MSE testing of advice rules based on surplus production models

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Report of the Eighth Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE VIII)

8–12 October 2018

Lisbon, Portugal

International Council for the Exploration of the Sea

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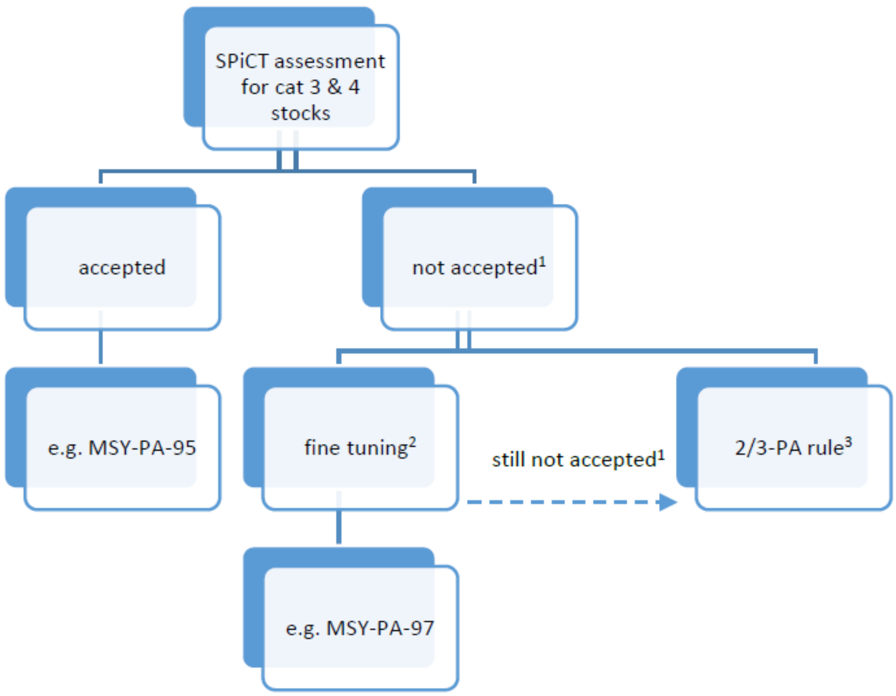
Executive summary

The Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for stocks in categories 3–6 (WKLIFE VIII), chaired by Carl O'Brien (UK) and Manuela Azevedo (Portugal) met in Lisbon, Portugal, 8–12 October 2018, to further develop methods for stock assessment and catch advice for stocks in categories 3–6, focusing on the provision of sound advice rules that are within the ICES MSY framework.

Two new MSY-based advice rules for the stochastic surplus production model in continuous time (SPiCT) have been investigated. While the first advice rule allows to scale the total allowable catch (TAC) according to the uncertainty of the assessment (MSY rule) specifying any fractile for the distributions: F/F_{MSY}, B_{pred}/B_{MSY}, C_{pred}, the second advice rule (MSY-PA) takes assessment uncertainty into account by including a precautionary buffer depending on the probability of the predicted biomass being below a given reference level (e.g. B_{lim}). To derive adequate advice rules for stocks suitable for a SPiCT assessment in categories 3 and 4 the following decision tree is proposed:



Additionally, the performance of the 3.2.1 catch rule can be improved in terms of risk by applying a multiplier. Last year in WKLIFE VII, based on a limited number of simulations (only four representative stocks), a multiplier of 0.95 was proposed independent of k. This year, to keep the probability of dropping below B_{lim} to 5% or less, and based on a larger number of stocks representing a wide range of life-history characteristics, simulations indicated a revision of this proposal incorporating k. If a multiplier were to be used independent of k, a multiplier of no greater than 0.8 is recommended. If a multiplier were to be used depending on the value of k, then for k values in the range of 0.08–0.19, a multiplier of no greater than 0.85 is recommended, and for k values in the range of 0.20–0.32, a multiplier of no greater than 0.90 is recommended. For k values above 0.32, the 3.2.1 catch rule should not be applied in its current form.

A number of harvest control rules (HCRs) using length-based indicators appropriate to the management of elasmobranch stocks were investigated prior to, and during, WKLIFE VIII. Simulation results based upon the cuckoo ray (*Leucoraja naevus* L.) are presented and future directions for work within WKLIFE are presented.

A number of promising approaches for short-lived species have been presented and discussed during both WKLIFE VII and WKLIFE VIII; however, the results are still preliminary, and the models require further improvement. To rectify this, a recommendation to convene an ICES Workshop of Data-limited short-lived species early next year (2019) has been proposed that addresses both assessment methods and long-term management strategy evaluations. Two co-chairs have been identified.

Lastly, it is recommended that there be a ninth meeting of WKLIFE in Lisbon, Portugal next year (2019), whose Terms of Reference should be discussed by ACOM at their November 2018 consultation meeting.

1 Introduction

1.1 Terms of reference

The Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for stocks in categories 3–6 (WKLIFE VIII), chaired by Carl O'Brien (UK) and Manuela Azevedo (Portugal) met in Lisbon, Portugal, 8–12 October 2018, to further develop methods for stock assessment and catch advice for stocks in categories 3–6, focusing on the provision of sound advice rules that are within the ICES MSY framework.

Specifically, the workshop was tasked with addressing the following Terms of Reference (ToRs):

a) Develop, test, and review advice rules that are in line with the ICES MSY and precautionary approaches for category 1 stocks that apply to a wide variety of ICES stocks (e.g. demersal species) in categories 3 and 4.

  i) Develop assessment methods that utilize a stock production model (e.g. SPiCT) and advice rules based on a short-term forecast (Section 3.1 of WKMSYCat34 report).

  ii) Develop assessment methods that utilize length-based approaches and advice rules of the form $\boldsymbol{C_{y+1}} = \boldsymbol{C_{current} r f b}$ (Sections 3.2.1 and 3.2.3 of WKMSYCat34 report).

    1) Test the advice rules via Management Strategy Evaluation (MSE).

    2) Establish whether performance of the advice rules is correlated with life-history characteristics.

    3) If such correlations exist, develop guidelines for use of the advice rules dependent on life-history characteristics.

  iii) Review all results via a formal ICES review process that provides ACOM with a product of proposed MSY and PA advice rules for category 3 and 4 stocks.

b) Develop, test, and evaluate assessment methods and on the basis for an advice rule for category 3 to 6 stocks for short-lived species.

  i) Consider the need for specific advice rules for these stocks, and if needed, test these advice rules via MSE.

WKLIFE VIII will report to ACOM no later than 9th November 2018.

1.2 Background

ICES provides advice on more than 260 stocks on an annual basis and more than sixty percent of these stocks are in categories 3–6. Further developments of the approaches used in providing advice on fishing opportunities for these stocks are needed. WKLIFE is the premier venue for method development and discussion of stock assessments and advice approaches for stocks in categories 3–6.

There is an increasing number of fish stocks in Categories 3 and 4 for which assessment of status relative to MSY proxy reference points is available but for which short-term forecasts and MSY-based advice are not available. At this year's meeting of WKLIFE, ICES wishes to further address this issue.

WKMSYCat34 (ICES, 2017) identified a suite of potential MSY-consistent advice rules for category 3 and 4 stocks. The rules need to be tested by Management Strategy Evaluation (MSE) in order to check that they perform adequately in terms of meeting MSY objectives; i.e. maximising long-term yield, in a manner that is consistent with precautionary principles; i.e. having a low probability of falling outside biologically sustainable limits. Specifically, commenting on each ToR:

ToR a) addresses these rules and their evaluation using either MSE or short-term forecasts, as proposed by ICES (2017).

Assuming a successful outcome for these evaluations, WKLIFE VIII will propose advice rules for the setting of catches in 2020 based upon scientific advice in 2019.

For the case of generic MSE testing and short-term forecasts, which consider overall general features instead of details of particular stocks, WKLIFE VIII continued the work initiated during WKLIFE VII.

ToR b) addresses the need for specific advice rules for stocks of short-lived species. The current advice rule for category 3–6 is targeted at stocks of medium- and long-lived species and has proven difficult to apply for stocks of short-lived species. With this ToR, WKLIFE VIII is requested to review available information on advice rules for these stocks and, if needed, to propose a specific advice rule for stocks of short-lived species.

1.3 Conduct of the meeting

The agenda for the workshop is presented in Annex A.

Much intersessional work had taken place ahead of the WKLIFE VIII meeting by participants, and this was presented during the first day and a half of the workshop. The presentations were used to define the work programme for the remainder of the workshop and the identification of *virtual* subgroups; three of which were identified:

- Subgroup 1 – focused on ToR a) i) iii);
- Subgroup 2 – focused on ToR a) ii) iii); and
- Subgroup 3 – focused on ToR b).

One participant worked by correspondence during the meeting and the facilities of Skype were relied upon for their full contribution to the workshop's subgroups and plenary discussions. This worked well, and lively discussions resulted from this interaction.

1.4 External review group

Prior to the WKLIFE VIII meeting, ICES secured an external review group for the work of the workshop; Chantel Wetzel (National Oceanic and Atmospheric Administration, USA) and Adrian Hordyk (University of British Columbia, Canada).

The science teams from DTU-Aqua, Denmark (dealing with SPiCT) and Cefas, UK (dealing with MSE) corresponded to the two reviewers ahead of the meeting; providing descriptions of their work and methods in preparation for the benchmark by the reviewers during WKLIFE VIII.

The reviewers attended the WKLIFE VIII meeting in Lisbon and fully participated in the plenary discussions and the further specification of simulation work undertaken during the week. The report of the external review group will be presented to ICES on 26th October 2018 and appended as the Annex 6 to this report.

1.5 Structure of the report

The structure of the report is as follows:

- Section 2 focuses on the activities of subgroup 1;
- Section 3 focuses on the activities of subgroup 2;
- Section 4 focuses on the activities of subgroup 3;
- Section 5 focuses on the MSE testing of catch rules for elasmobranchs;
- Section 6 focuses on future directions of work for data-limited stocks (DLS).

Instead of providing conclusions from the workshop at the end of the report, each of the Sections 2–5 provides a synthesis of the material presented within each Section in either a conclusions, recommendations or future directions Section. The reviewers in their report, appended to this report as Annex 6, incorporated recommendations for future research but these have not been further incorporated into the WKLIFE VIII report and need to be considered in all future work.

1.6 Follow-up process within ICES

The participants at WKLIFE VIII agreed to provide text for the draft workshop report by Friday 19th October 2018 and to then comment on the compiled draft report no later than 26th October 2018; when the report can be formatted by the ICES Secretariat.

The report of the external review group will be presented to ICES no later than 9th November 2018 and appended as the Annex 3 to this report.

<u>Recommendation</u>: It is recommended by WKLIFE VIII that there be a ninth meeting of WKLIFE in Lisbon, Portugal 30 September–4 October 2019, whose ToRs should be discussed by ACOM at their November 2018 consultation meeting.

1.7 References

ICES. 2017. Report of the Workshop on the Development of the ICES approach to providing MSY advice for category 3 and 4 stocks (WKMSYCat34). ICES CM 2017/ACOM:47.

2 MSE testing of advice rules based on surplus production models

2.1 Introduction

ICES category 3 and 4 stocks (hereafter referred to as data-limited stocks; ICES, 2012) are currently managed by use of the two over three rule (2/3 rule; ICES, 2017a). The 2/3 rule is based on the trend in survey index (last two years divided by the preceding three years), together with an uncertainty cap, which limits the change in the advice between 80% and 120% relative to the TAC in the preceding year, and incorporates an additional precautionary buffer. The PA buffer is only included in the 2/3 rule if the estimation of F_{MSY} and B_{MSY} proxy levels is possible and describes the application of a 20% TAC reduction (maximum every three years) if the stock is classified as overfished regarding biomass ($B/B_{trigger}$) or fishing mortality (F/F_{MSY}; ICES, 2018a). However, data-limited stocks are also suitable for the assessment with surplus production models, such as the stochastic production model in continuous time (SPiCT; Pedersen and Berg, 2017), which is a re-parameterized version of the Pella-Tomlinson surplus production model (Pella and Tomlinson, 1969). The model quantifies observation and process noise and estimates stock status and reference levels with associated confidence intervals.

The Workshop on the Development of the ICES approach to providing MSY advice for category 3 and 4 stocks (WKMSYCat34; ICES, 2017a) suggested a specific case of equations 2.1 and 2.2 for management advice based on SPiCT assessments with f = 0.5, corresponding to the median of the three distributions (F/F_{MSY}, $B_{pred}/B_{trigger}$, C_{pred}). However, it was pointed out by ICES WKLife VII (ICES, 2018b) that this advice rule does not consider assessment uncertainty, which can be substantial depending on the quantity and quality of available data (see e.g. pp. 194–198 in ICES, 2017b). WKLife VII concluded that the assessment uncertainty has to be accounted for and proposed to choose a fractile less than 0.5 (from here on referred to as the MSY rule). By considering any fractile of the three distributions less than 0.5, the uncertainty of estimated stock status in terms of relative fishing mortality and biomass is accounted for and the advice more conservative than the median advice rule (ICES, 2018b).

Equation 2.1

$$TAC_{y+1} = \Phi^{-1}{}_{(C_{pred}|F=F_y \ldots F_{y+1})}(f)$$

Equation 2.2

$$F_{y+1} = F_y \, \frac{\min\left(1,\ \Phi^{-1}{}_{\left(\frac{B_{y+1}}{B_{trigger}}\right)}(f)\right)}{\Phi^{-1}{}_{\left(\frac{F_y}{F_{MSY}}\right)}(f)}.$$

where $B_{trigger}$ is defined as $0.5B_{MSY}$ (ICES, 2018a), Φ is the inverse distribution function such that $\Phi^{-1}{}_{C_{pred}}(f)$ means the fth fractile of the C_{pred} distribution, and f is a chosen fractile less than or equal to 0.5.

In addition to the updated MSY rule, an extended version of the MSY rule with a precautionary buffer (Eq. 2.3) is introduced here (referred to as MSY-PA rule hereafter).

Equation 2.3

$$TAC_{y+1} = \begin{cases} \Phi^{-1}{}_{(C_{pred} \mid F=F_{MSY})}(f) & if P\left(B_{pred} \mid F = F_{MSY} < B_{lim}\right) \leq (1 - P_{PA}) \\ \Phi^{-1}{}_{(C_{pred} \mid F=F_{opt})}(f) & if P\left(B_{pred} \mid F = F_{MSY} < B_{lim}\right) > (1 - P_{PA}) \end{cases}$$

where F_{opt} is an F value such that $P\left(B_{pred} \mid F = F_{opt} < B_{lim}\right) = (1 - P_{PA})$, B_{lim} is defined as $0.3B_{MSY}$, and P_{PA} representing the probability of the predicted biomass being above B_{lim} and thus $(1 - P_{PA})$ being the accepted risk level (by convention 5%). A textual description of the MSY-PA rule is as follows:

1) Make a one year forecast where F is kept at F_{MSY}, and evaluate the probability of being above B_{lim} after one or two years (dependent on assessment period).
2) If the probability is greater than (1-P_{PA}) then accept forecast using F=F_{MSY}, else go to 3.
3) Solve for a reduced F, such that the probability of being above B_{lim} after one or two years is equal to (1-P_{PA}). This equation may have no solution for depleted stocks because the probability is lower than (1-P_{PA}) for all values of F including zero. In this case TAC_{y+1} = 0.
4) Apply stability clause controlling the TAC variability between years (optional; see below).

The PA rule is comparable to the MSY rule with corresponding fractiles, but allows in addition to control the accepted risk of the biomass falling below B_{lim} taking assessment uncertainty into account. In theory, the MSY-PA rule can be combined with the fractile rule in that instead of the median any fractile of the distributions are considered, however, this is not explored within the frame of this study. All SPiCT-based advice rules include a stability clause, which is comparable to the uncertainty cap of the 2/3 rule stabilizing catch advice and limiting the variation of TAC from one year to the next between an upper and lower boundary (which can be specified). The MSY and MSY-PA approach are implemented and available in the SPiCT package on GitHub at https://github.com/tokami/spict/tree/wklife8. The respective function (called get.MP) has 15 arguments and allows to generate any combination of SPiCT based advice rules. In addition to defining the fractiles and the precautionary buffer, it allows to define the stability clause, setting the assessment interval and the time-step of the Euler discretization (dt_{euler}; for more information see the help file of the function help(get.MP)).

Based on equations 2.1–2.3 a range of SPiCT-based advice rules were defined (Table 2.1). The performance of the advice rules relative to each other, to two 2/3 rules (2/3 with and without PA buffer), to an advice rule corresponding to no fishing, and to an advice rule corresponding to 'optimal' fishing (fishing according to F_{MSY} based on the operating model with perfect knowledge) was evaluated within a MSE framework (see below).

Table 2.1. SPiCT-based advice rules.

Advice rule	Fractile C_{pred}	Fractile F/F_{MSY}	Fractile B_{pred}/B_{MSY}	PA	P_{PA}	Stability clause (SC)	SC level
1	0.5	0.5	0.5			✔	0.5
2	0.49	0.49	0.49			✔	0.5
3	0.47	0.47	0.47			✔	0.5
4	0.4	0.4	0.4			✔	0.5
5	0.35	0.35	0.35			✔	0.5
6	0.4	0.4	0.4			✔	0.2
7	0.4	0.4	0.4				
8	0.5	0.5	0.5	✔	0.4	✔	0.5
9	0.5	0.5	0.5	✔	0.8	✔	0.5
10	0.5	0.5	0.5	✔	0.85	✔	0.5
11	0.5	0.5	0.5	✔	0.9	✔	0.5
12	0.5	0.5	0.5	✔	0.95	✔	0.5
13	0.5	0.5	0.5	✔	0.97	✔	0.5
14	0.5	0.5	0.5	✔	0.99	✔	0.5

2.2 MSE simulations

The relative and absolute performance of the advice rules was evaluated within an MSE framework (Smith, 1994). The DLMtool package (Carruthers and Hordyk, 2018a) was used for the MSE simulations, as it is particularly tailored to data-limited conditions (Carruthers and Hordyk, 2018b).

Three stocks representing three different life-history strategies were chosen with biological parameters based on Jardim *et al*. (2015): (i) anchovy in Biscay-Iberia (AN) representing a short-lived species, (ii) haddock in the Celtic Seas (HA) representing a medium-lived species, and (iii) widely distributed ling (LI) representing a long-lived species. The biological parameters of these stocks are summarized in Table 2.2.

Table 2.2. Most important average life-history parameters for the three stocks (anchovy - AN, haddock -HA, ling -LI).

Parameter	AN	HA	LI
L_∞	23	79.9	119
K	0.44	0.2	0.14
t_0	-0.1	-0.36	-0.1
M	0.86	0.32	0.26
maxage	11	32	51
L_{50}	16.8	30.1	74
$L_{50\text{-}95}$	2.2	9	7.8

A uniform distribution was defined around the average parameters: L_∞, K, t_0, L_{50}, $L_{50\text{-}95}$, where the range was defined by a coefficient of variation (CV) of 5%. The age-dependent natural mortality (M) was calculated by means of the equation after Gislason (2010) and an upper and lower bound of the uniform distribution defined with a CV of 5%. The Beverton and Holt stock–recruitment-relationship (Beverton and Holt, 1957) was assumed for all stocks, with varying steepness parameters (h) of 0.5, 0.75 and 0.9 for the three stocks (AN, HA, LI) respectively and a uniform distribution with a CV of 5%. Autocorrelation of the residuals was bound between 0.5–0.7, and recruitment variability σ_R('Perr' in DLMtool) between 0.2–0.4. The range of the selectivity parameters was standardized as a fraction of the length-at-maturity (L_{50}), with $L_5 = (0.2 - 0.4)\, L_{50}$ and $L_{FS} = (0.75 - 1.1)\, L_{50}$.

A baseline scenario was defined with following MSE settings:

- Historic years = 50 (used for SPiCT assessment: 40 years);
- Projection years = 50;
- Number of simulations = 200;
- Depletion level in last historic year: above B_{MSY};
- Effort time-series in historic years: roller coaster (two-way trip);
- Observations with low noise level (0.15);
- No implementation error;
- Biannual assessment and advice interval;
- Euler discretization time-step: $dt_{euler} = 1/4$ (corresponds to a model with quarterly time-step).

Based on the baseline scenarios, five additional scenarios exploring individual aspects by changing one assumption at a time were defined as follows:

- Baseline;
- Depletion level around B_{lim};
- Depletion level around B_{lim}, high observation noise;
- Depletion level around B_{lim}, high observation noise, 20 years of data;
- Depletion level around B_{lim}, high observation noise, 20 years of data, one-way effort time-series;
- Depletion level around B_{lim}, high observation noise, 20 years of data, one-way effort time-series, annual advice.

Figure 2.1 shows the effort time-series and used data for the different scenarios.

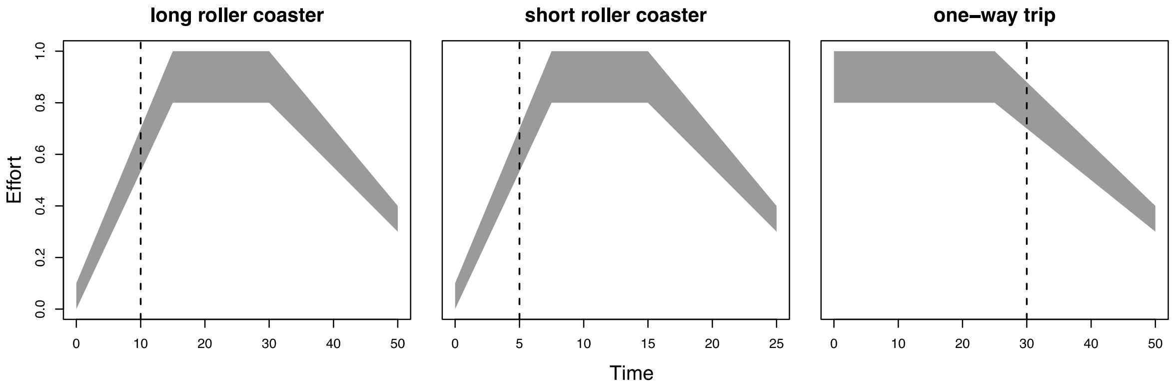


Figure 2.1. Three different effort time-series for the historic years (long and short roller coaster and one-way trip). The vertical dashed lines represent the part of the time-series available to the SPiCT assessment (year 10–50 or year 5 to 25).

The different depletion levels in the last historic year for the three stocks are shown in Figure 2.2.

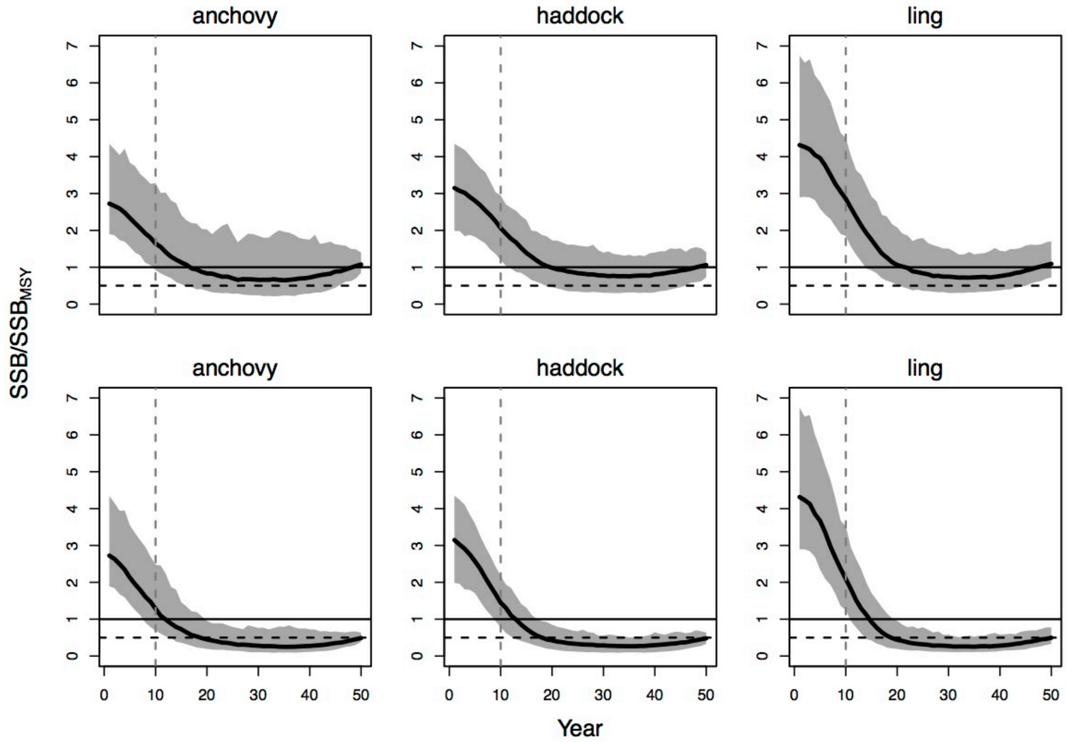


Figure 2.2. Trajectories of relative spawning–stock biomass (SSB/SSB$_{MSY}$) for all stocks and two different depletion levels (above B$_{MSY}$ and around B$_{lim}$) in the last historic year in the first and second row, respectively. Horizontal dashed line shows B$_{lim}$ and vertical dashed line indicates the part of the time-series which was used for the SPiCT assessment (year 10–50 for scenarios 1–3).

The observation model build into DLMtool was modified by defining the observation error for the catch and index time-series as 0.15 and 0.3 for the low and high noise scenarios respectively. Furthermore, any additional bias was removed and beta (the parameter determining hyperstability/hyperdepletion) was set to 1, which is equal to assuming a proportional relationship between stock biomass and the survey index.

A second simulation framework with SPiCT as the simulation and estimation model allowed to generate theoretical stocks with different shape parameters (n) for the production curve (Figure 2.3). These stocks were then assessed with SPiCT using a variety of priors on the shape parameter to assess the effect of tightening and misspecifying the prior on the performance of the assessment method and thus the advice rules. Four stocks with four different n parameters (0.6, 1.2, 2, 3.5) were generated and assessed with no prior, and priors assuming a normal distribution with $mean = log(2)$, and four different standard deviations: 2, 1, 0.1, 0.01.

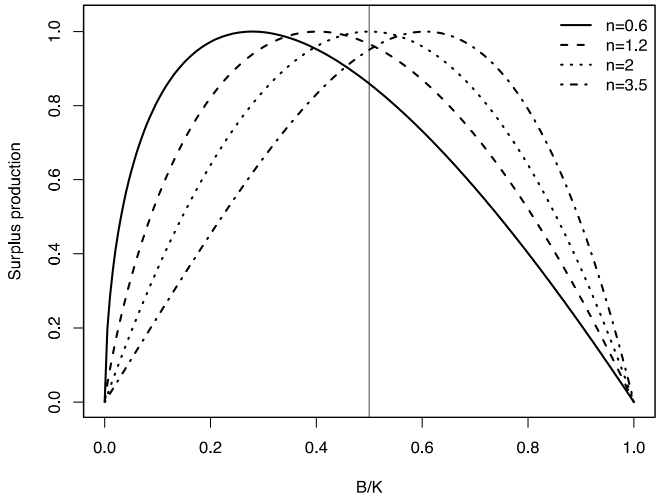


Figure 2.3. Production curves for the four simulated theoretical stocks with different n parameters (0.6, 1.2, 2, 3.5).

The performance of all advice rules between different scenarios and stocks was compared based on following performance metrics:

- Risk 1: average probability that SSB is below B_{lim} where the average (of the annual probabilities) is taken across x number of years (ICES, 2013), which was calculated over three different time periods (year 1–50, 1–5, 25–50) to account for differences in the overall performance, the speed of recovery, and the long-term performance, respectively.
- Mean relative yield (C/Y_{ref}) where $Y_{ref} = C_{F_{MSY},ny-5}$ (Carruthers and Hordyk, 2018c).
- Coefficient of variation (CV) of yield.
- Time to $P(B_{pred} > B_{lim}) > 0.95$.

2.3 Results and discussion

The different SPiCT-based advice rules show an overall good performance with a high average relative yield of around 80% and risk levels around the 5% threshold for haddock (Figure 2.4) and a generally small proportion of non-converged runs of less than 8%. While the 2/3 rules can generate a mean relative yield of around 60% in scenarios with low observation noise (scen1 & scen2), the percentage decreases to 40% and less for the remaining scenarios, while the yield generated with SPiCT remains high for all scenarios (Figure 2.4). Across all scenarios and species, the 2/3-PA rule outperforms the 2/3 rule without precautionary buffer in terms of risk, while yield levels are similar.

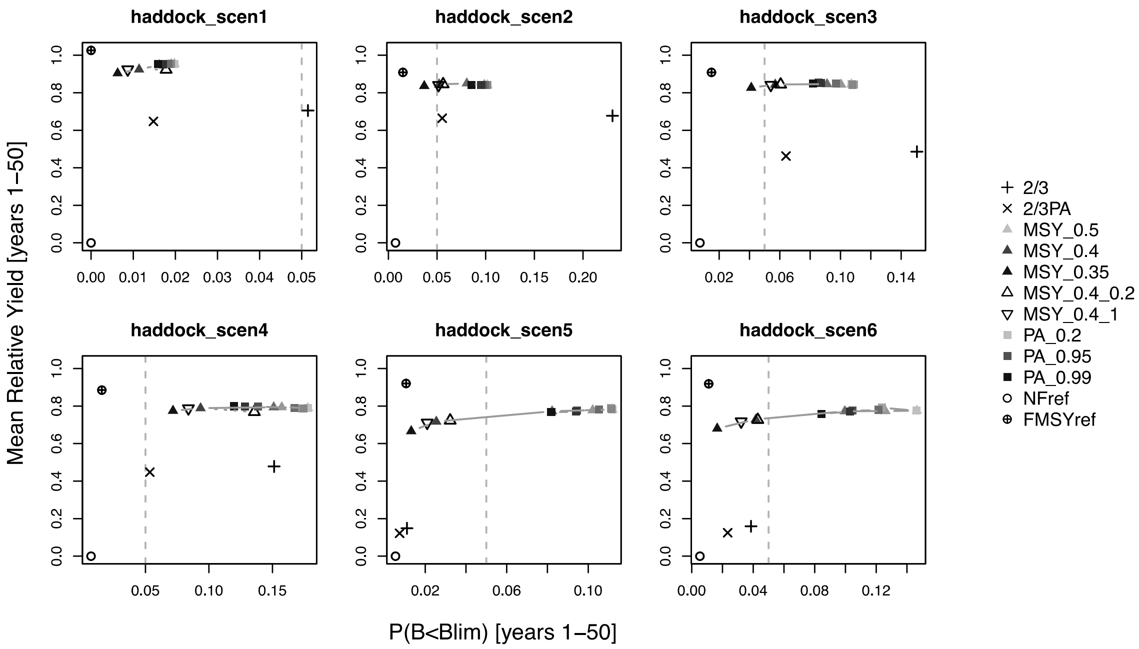


Figure 2.4. Trade-off graph of mean relative yield and risk 1 for haddock over all projection years (1–50) and all scenarios with $^2/_3$ and reference rules (NFref & FMSYref). Vertical dashed line represents the reference risk level of 5%. Solid lines between advice rules display the connection of common advice rules which only differ in the fractile or P_{PA}. Intermediate fractile levels not displayed in the legend can be found in Table 2.1.

The advice rule with perfect knowledge (FMSYref) demonstrates the importance of the relative comparison among advice rules, as even with perfect knowledge generated yield is not 100% and risk not equal to 0, which is partly attributed to the fact that most scenarios start from an overexploited stock which takes time to recover. Absolute reference levels, such as the 5% reference level for risk 1 should therefore be corrected for the risk of FMSYref. For scenarios with a shortened time-series (20 years), the $^2/_3$-PA rule has a lower risk than most MSY and MSY-PA rules. Although this difference is reduced when considering the long-term performance (years 25–50; Figure 2.18), it demonstrates that the short-time-series (scenario 4–6) limits the performance of the MSY and MSY-PA rules. In those situations the $^2/_3$-PA rule informed by SPiCT poses the more precautionary advice rule, although it cannot generate a good yield (10–50%). The two other stocks (anchovy and ling) show the same patterns between the $^2/_3$ rules compared with MSY and MSY-PA rules, while the risk for anchovy is slightly higher (cp. for anchovy: Figure24 in Section 4.2 and for ling: Figure 2.16 in Section 2.7).

Figure 2.5 reveals that there are substantial differences between the MSY and MSY-PA rules with different fractiles and P_{PA} levels, respectively. While for scenarios 1 to 4 the differences are mainly concerning the risk levels, scenario 5 and 6 show the trade-off between yield and risk. Lower fractiles and higher P_{PA} levels do not only lead to a reduction of risk, but also to a reduction of yield (Figure 2.5) for those scenarios. These patterns demonstrate the important effect of the consideration of assessment uncertainty in advice rules on risk and yield levels.

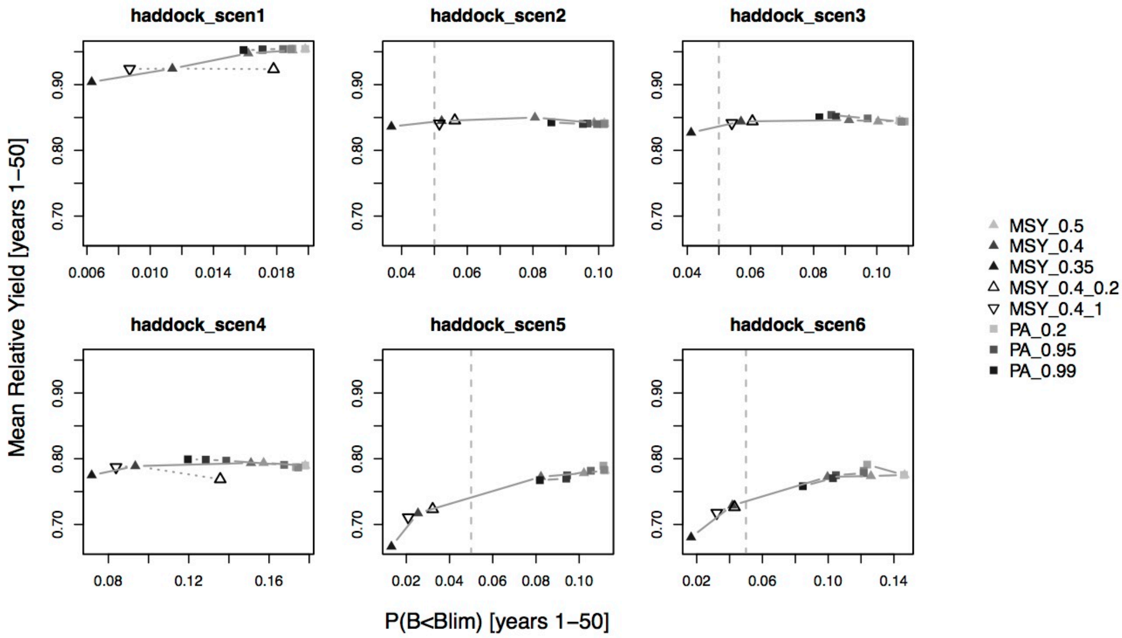


Figure 2.5. Trade-off graph of mean relative yield and risk 1 for haddock over all projection years (1–50) and all scenarios without ²/₃ and reference rules (NFref & FMSYref). Vertical dashed line represents the reference risk level of 5%. Solid lines between advice rules display the connection of common advice rules which only differ in the fractile or P_{PA}. Intermediate fractile levels not displayed in the legend can be found in Table 2.1.

Removing the stability clause leads to a lower risk (open triangle on its head in Figure 2.5), demonstrating that the stability clause confines the SPiCT-based advice rules in terms of risk, however, stabilizes TAC in terms of advice (and catch) variability (open triangle on its head in Figure 2.6), while a tighter stability clause (of 20%) has the opposite effect (open triangle in Figure 2.5 and Figure 2.6). An intermediate stability clause with a level of 50% seems like a good trade-off between acceptable risk levels and meaningful variability of catch advice. As expected, the trade-off between yield and CV of yield is opposite to the trade-off between yield and risk with lower fractiles and higher P_{PA} levels showing higher CVs (Figure 2.6). From a management perspective, high variability of annual yield (here equal to TAC as no implementation error was incorporated) due to assessment model performance should be avoided.

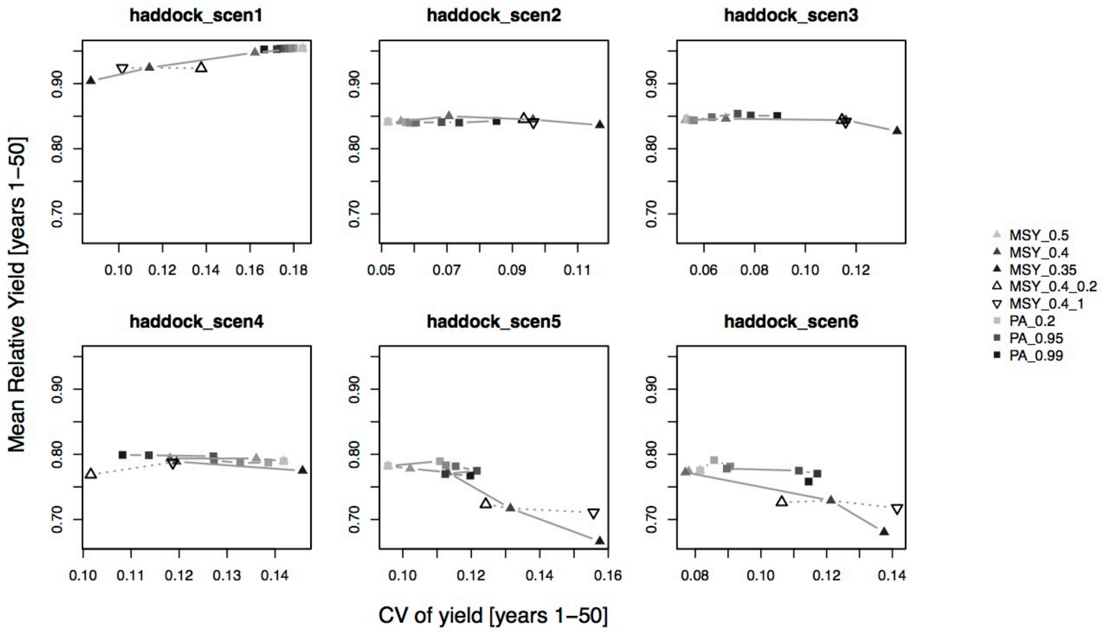


Figure 2.6. Trade-off graph of mean relative yield and coefficient of variation of yield for haddock over all projection years (1–50) and all scenarios without ²/₃ and reference rules (NFref & FMSYref). Vertical dashed line represents the reference risk level of 5%. Solid lines between advice rules display the connection of common advice rules which only differ in the fractile or P_{PA}. Intermediate fractile levels not displayed in the legend can be found in Table 2.1.

The average risk trajectory over time reveals the reasons for the relative high risk for the MSY-PA rules in scenarios 4–6. Across all three stocks, the two MSY-PA rules and ²/₃-PA rule - displayed here - show an increase or plateau in risk over the first years (Figure 2.7), indicating that the data quantity (20 years) together with the poor data quality (here: low contrast & high observation noise) in the first projection years is hardly sufficient for a meaningful SPiCT assessment and only after 10–15 years SPiCT drives the stock towards the threshold of 5% (bound by the stability clause), around which the risk seems to stabilize towards the end of the time-series. This pattern also explains the dependence of the performance on the projection time period in consideration. The risk trajectory for scenario 3 (first row in Figure 2.7) show a faster decline of risk levels.

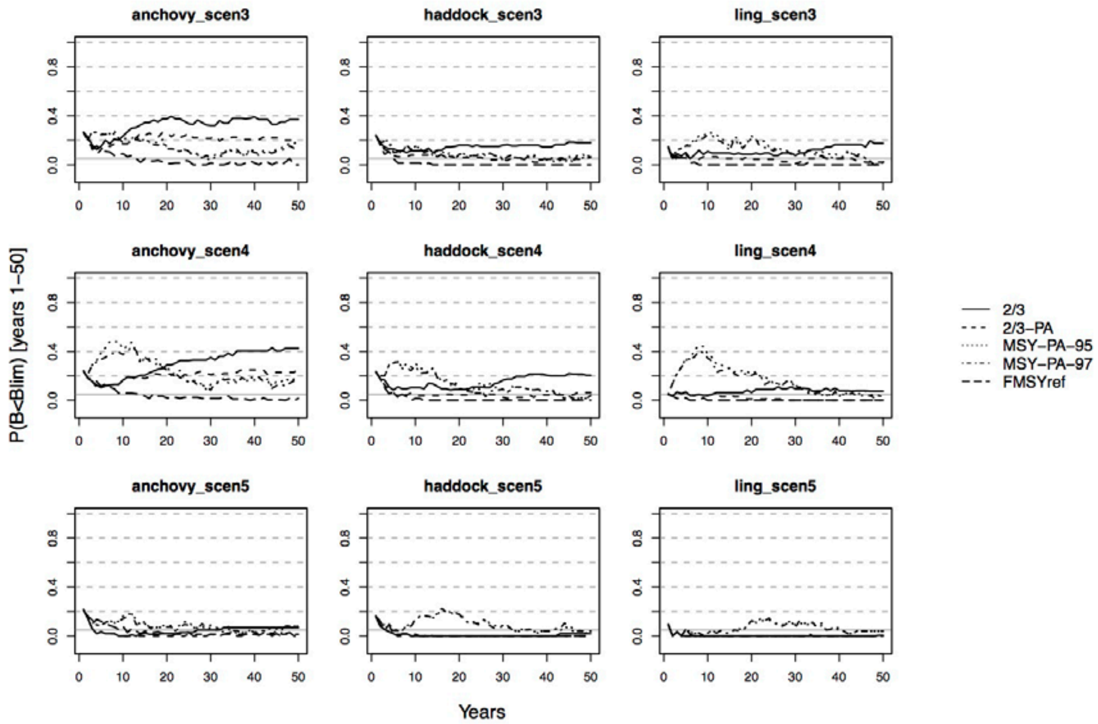


Figure 2.7. Average risk trajectories over projection years (1–50) for a selection of advice rules, all stocks and scenarios 3–5.

The simulations with increased process noise in the operating model (higher levels of recruitment variability - σ_R) show that the absolute risk levels increase for all MSY and MSY-PA rules, while the yield levels remain similar or are slightly reduced (Figure 2.8). The relative pattern between advice rules with different fractiles and P_{PA} levels remains consistent. The results indicate that tightening the prior in this specific case yields to a decrease in the risk and a larger proportion of converged runs: Number of non-converged runs decreases from 4.1%, 6.6%, 7.5% to 0.1%, 0.2%, 0.3%, for the three σ_R levels respectively. Although the prior is set to mean n=2 and the haddock stock shows a clearly lower n level (even below n=1; Figure 2.19), the performance of the advice rules is improved. As with the other results, these findings are consistent across all stocks (see Figure 2.20 and Figure 2.21). The simulations also show that the yield with MSY-PA rules is higher than with MSY rules across all levels of recruitment variability.

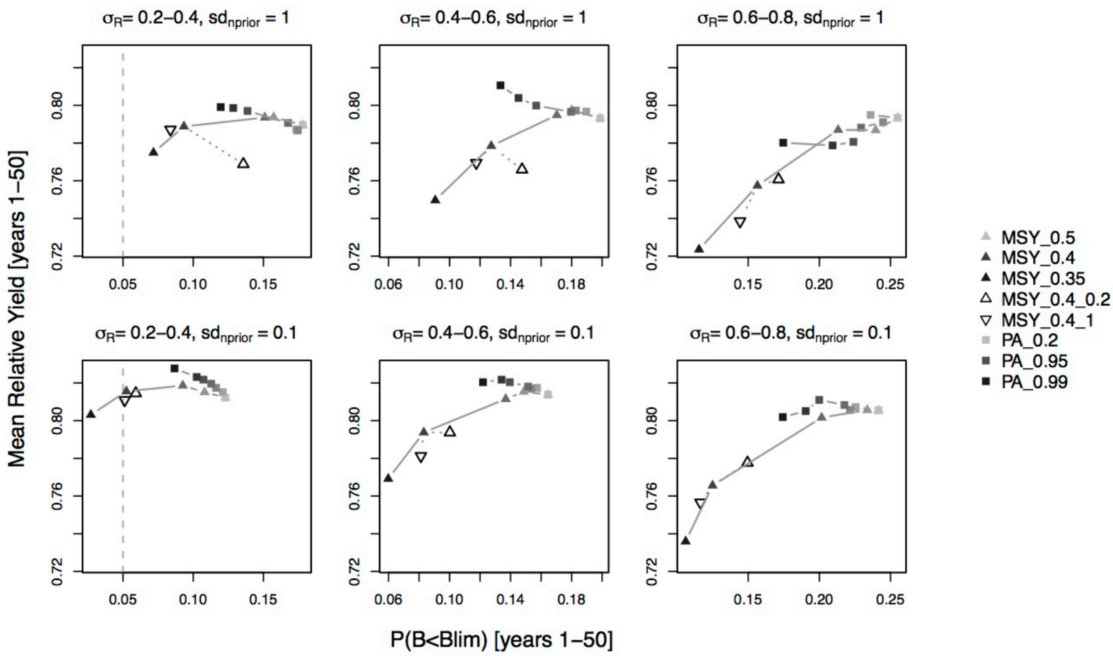


Figure 2.8. Trade-off graph of mean relative yield and risk 1 for haddock over all projection years (1–50) for three levels of recruitment variability (σ_R; columns) each with two different priors for the shape parameter of the production curve (rows). Based on the haddock stock and scenario 4. Vertical dashed line represents the reference risk level of 5%. Solid lines between advice rules display the connection of common advice rules which only differ in the fractile or P_{PA}. Intermediate fractile levels not displayed in the legend can be found in Table 2.1.

Figure 2.9 shows that the Euler discretization time-step (dt_{Euler}) affects the yield and risk level of all three tested sets of SPiCT-based advice rules (MSY-0.5 rule, MSY-0.4 rule, MSY-PA-95). However, the biggest difference is between a dt_{Euler} of 1 and a dt_{Euler} of $^1/_4$, while the differences between smaller time-step sizes are negligible.

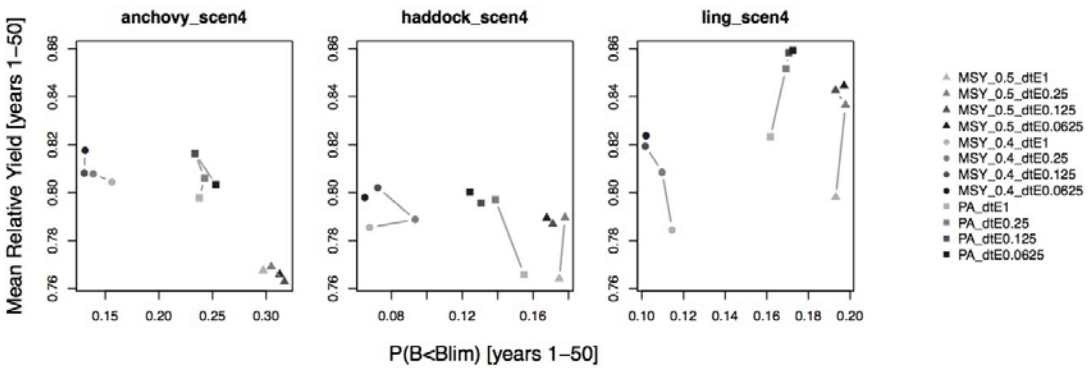


Figure 2.9. Trade-off graph of mean relative yield and risk over all projection years (1–50) for three sets of advice rules (median MSY, 0.4 fractile MSY, and MSY-PA rules) each with four different levels of dt_{Euler} (1, ¼, $_1/^8$, $_1/^{16}$) for all species and scenario 4.

The simulations regarding the information content and misspecification of the prior on n, demonstrate that the informative prior (here 0.1) can help model performance in terms of reducing the estimation error of relative states and reducing the size of confidence intervals compared with the assessment without prior (Figure 2.10).

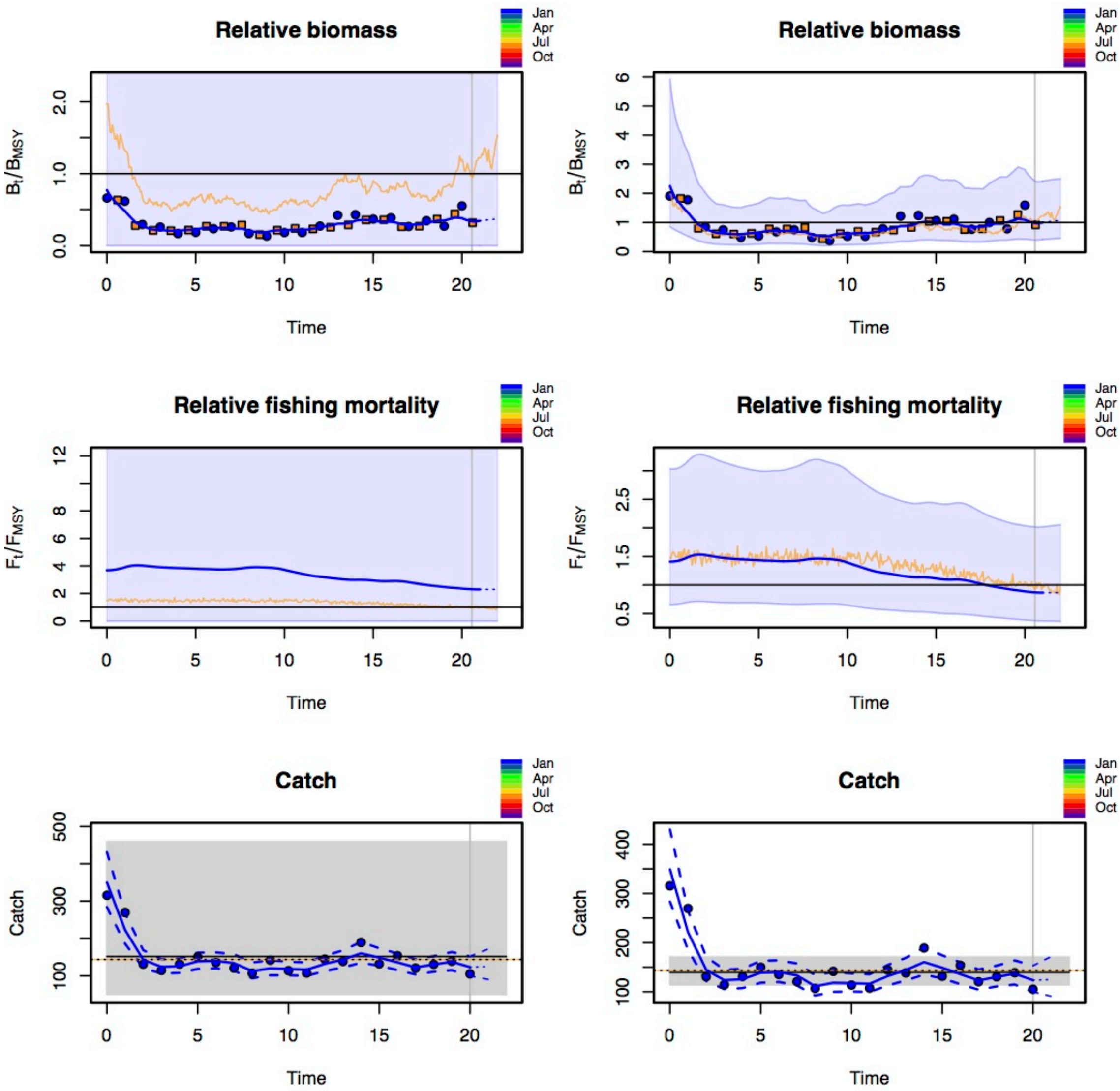


Figure 2.10. Two SPiCT assessments with a theoretical stock with n = 2, where the first column used a no prior on n and the second column used a prior of 0.1.

The gradual improvement of model performance (decreasing error and decreasing confidence intervals) by use of a prior with increasing information content for the stock with n =2 is also obvious in Figure 2.11. However, this pattern does not necessary hold anymore, if the prior is misspecified and tightened: For the n=0.6 stock the confidence intervals do not decrease and for n=3.5 the confidence intervals even increase with decrease prior. However, for all theoretical stocks the tighter prior helps model convergence (n=1.2 & n=3.5 without prior do not converge) and decrease the estimation error in F/F_{MSY} and B/B_{MSY} (Figure 2.22). The estimation error for the relative states decreases although the misspecified tight prior on n determines the estimated value of n (Figure 2.23).

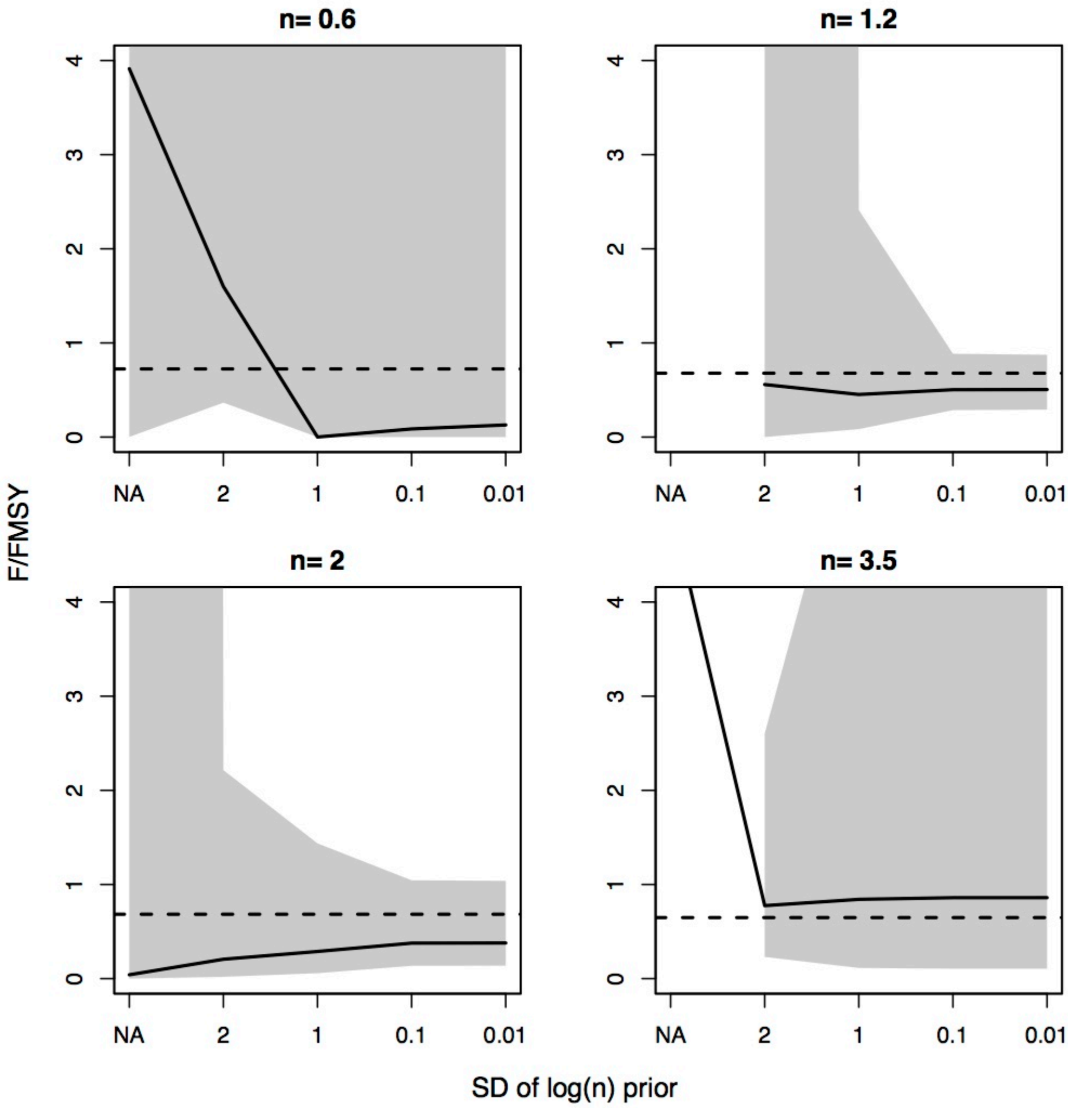


Figure 2.11. Relative fishing mortality (F/F_{MSY}) for different priors for all simulated stocks. Shaded areas represent 95% confidence intervals and dashed horizontal line represents true F/F_{MSY} level.

2.4 Conclusions

Within the context of WKLife VIII, two new MSY-based advice rules for the stochastic surplus production model in continuous time (SPiCT) have been introduced and made publicly available (https://github.com/tokami/spict/tree/wklife8). While the first advice rule allows to scale the TAC according to the uncertainty of the assessment (MSY rule) specifying any fractile for the distributions: F/F_{MSY}, B_{pred}/B_{MSY}, C_{pred}, the second advice rule (MSY-PA) takes assessment uncertainty into account by including a precautionary buffer depending on the probability of the predicted biomass being below a given reference level (here: B_{lim}).

The risk of all SPiCT based advice rules is around or slightly above 5% (between 0.1% and 10%) for all scenarios of the medium and long-lived species in the last 25 years of the projection time-series (Figure 2.18), for short-lived species the risk increase up to 20% for two scenarios. The mean relative yield is twice as high with MSY and MSY-PA rules compared with ²/₃ rules across all scenarios and stocks. The ²/₃ rule with the PA buffer outperforms the standard 2/3 rule without buffer in terms of risk, but has similar relative yield levels. The absolute performance of the MSY and MSY-PA rules is a function of the fractiles and the P_{PA} used. Different fractiles/P_{PA} levels impact the:

- Trade-off between yield and risk;
- Trade-off between yield and variability of yield;
- Time to $P(B_{pred} > B_{lim}) > 0.95$.

Absolute levels of risk, average relative yield, and CV of yield for advice rules with different fractiles and P_{PA} levels vary between stocks (life-history traits) and scenarios (data quality and quantity). However, the relative performance of different advice rules (relative pattern between different fractiles or P_{PA} levels) is similar for different life-history strategies (short-, medium-, long-lived species), different lengths of time-series (40 vs. 20 years), effort time-series (roller coaster vs. one-way trip), observation noise levels, and process noise in the operating model. The MSY-PA rules have comparable yield and risk levels to the MSY rules with fractiles between 0.45–0.5. Fractiles below 0.45 lead to a reduction of risk levels, but also to associated decrease in average relative yield levels. Results show, that short-time-series (20 years) and the one-way effort trip decrease the performance of SPiCT and slight increase of risk levels (with similar yield levels). The results revealed slight differences between annual and biennial assessments, in particular for short-lived species, where annual assessment led to lower risks. The parameter dt_{Euler} impacts the absolute levels between of yield and risk, with the biggest difference between values of 1 and 1/4 and only slight differences between 1/4, 1/8, and 1/16, supporting the sufficiency of dt_{Euler} $1/4$ for this simulation study. Number of non-converged runs differs between scenarios, stocks and advice rules, but are generally low with less than 9%. Higher process noise in the operating model (recruitment variability) increases absolute risk levels and impacts relative performance of advice rules, which can partly be attributed to the increased number of non-converged runs (from 7% to 10%) and the convention of using last year's advice for these runs. The MSY-PA rules show higher yield levels for the high process noise scenarios, indicating higher robustness and consistency than MSY rules. A tighter prior on parameter 'n' can helps convergence, but decreases confidence intervals and might lead to bias, thus impacting the recommended TAC by advice rules, which take assessment uncertainty into account (MSY and MSY-PA rules).

All results are dependent on the assumptions of the operating model (see ICES, 2018b). In particular regarding short-lived species, which are driven by recruitment and show high values of recruitment variability, the results of this simulation study have to be evaluated under consideration of the model assumptions (e.g. yearly time-step). Furthermore, absolute values of the performance metrics are dependent on the settings of the MSE framework and assessment model, such as the number of simulations for each scenario (200), the number of projection years (50), noise levels in the operating model, performance metrics (year 1–5 vs. year 25–50), and the Euler discretization time-step (¼). However, the results show that the number of simulations is adequate (Figure 2.13, Figure 2.14, Figure 2.15), that a dt_{Euler} of ¼ is adequate and should be the upper limit (dt_{Euler} of 1 can highly affect performance metrics; Figure 2.9), and that different time periods for the performance metrics should be evaluated and can give different insights about the performance of advice rules (short-term recovery vs. long-term sustainability).

Based on the results presented here, MSY-PA advice rule, e.g. MSY-PA-95 with a stability clause (±50%) can be recommended as overall well-performing advice rules for SPiCT assessments. This decision was based on following points: (i) The advice rules are more conservative than the median advice rule suggested by WKMSYCat34; (ii) They take assessment uncertainty into account (observation and process noise of the model and uncertainty of estimated reference points); (iii) They show high yield levels and more consistent patterns for high levels of recruitment variability of the operating model than the MSY rules. Different values for P_{PA} ca be considered, which should be adopted on a stock-by-stock basis. Lower values could for example be reasonable due to socio-economic reasons when a (close to) zero TAC is unacceptable, or if there is other evidence not utilized by SPiCT, that indicate a healthy stock status. Higher P_{PA} values could be considered if some model assumption(s) are known to be seriously violated. The use of priors, in particular for hard to estimate parameters (e.g. n; Wang *et al*., 2014; Thorsen *et al*., 2012) should be considered to help model convergence. In the best case, no priors are needed, however, if data quality and quantity reach the limits of SPiCT requirements (scenarios 4, 5 and 6), priors with varying degree of information content can be used and results compared with each other. However, caution is required as a more informative prior affects the width of the confidence intervals and thus the recommended TAC. In order to account for the decreased confidence bounds, it is recommended to use a more conservative advice rule, such as e.g. MSY-PA-97 with stability clause (±50%) when tight priors on n are used (tighter than sd=2). The stability clause of ±50% is recommended for all SPiCT advice rules, stabilizing catch advice while allowing flexibility. If a SPiCT assessment is not accepted even after fine tuning (see Figure 12), the 2/3-PA rule should be used for management advice, where the F_{MSY} proxy can be derived from various methods, such as length-based methods and indicators or catch-only methods. Despite these general recommendations concerning SPiCT-based advice rules, case-specific MSEs are needed and should be used for the evaluation and comparison of a set of advice rules. The recommendations can be summarized with the decision tree in Figure 2.12to derive adequate advice rules for stocks suitable for a SPiCT assessment in categories 3 and 4.

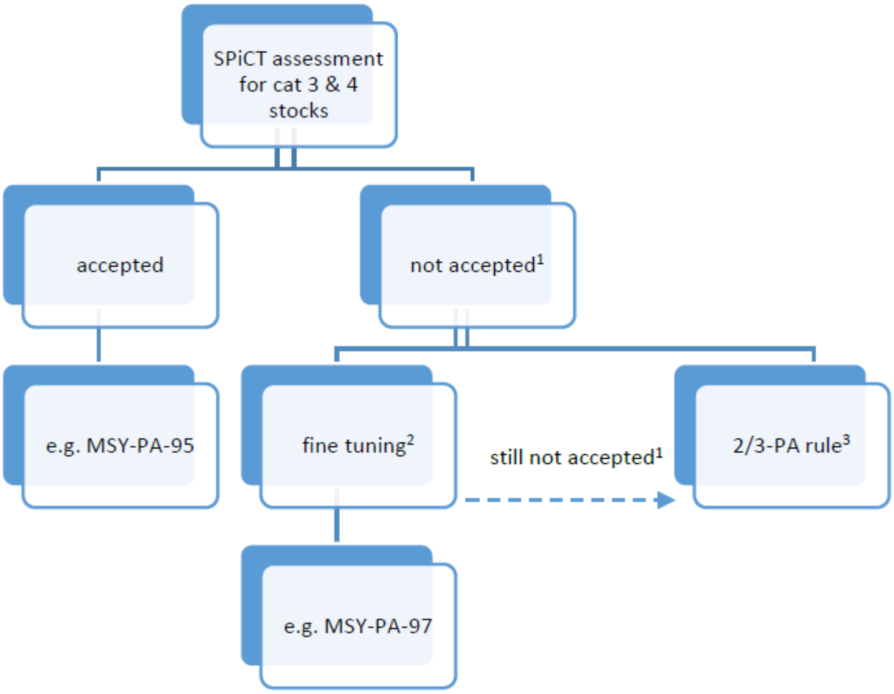


Figure 2.12. Decision tree for SPiCT assessment of ICES category 3 & 4 stocks, with following annotations: [1] a set of guidelines (see below) assists working groups with the decision of the acceptance and rejection of individual SPiCT assessments; [2] e.g. tighter prior on n; [3] with an F_{MSY} proxy from alternative assessment methods, such as length-based methods, or catch only models.

Important criteria as guidance for SPiCT assessment acceptance:

- Model converged (`res$opt$convergence == 0`);
- All parameter uncertainties could be estimated (`!any(is.infinite(res$sd))`);
- No violation of model assumptions (`spictplot.diagnostics(res)`);
- Consistent trend in the retrospective analysis (`ret <- fit.retro(res)`);
- Non-influential starting values (`check.ini(res)`);
- Meaningful biological and fisheries-related parameters (K, r, B_t, F_t);
- Meaningful confidence intervals (not too large).

where 'res' is the object with the results of the SPiCT assessment (res <- fit.spict(inp)). If any of these points is not fulfilled, the assessment in its current state should be rejected and a fine tuning of the SPiCT assessment should be considered. In particular, tightening the prior on n can help model convergence and performance, but other tuning procedures should also be considered, such as defining outliers or expected noise levels for input data, etc. (for more information see the SPiCT manual at https://github.com/tokami/spict/blob/wklife8/spict/vignettes/vignette.pdf.

2.5 Future work

The SPiCT-based advice rules should be implemented within another MSE framework. This would allow to compare the here presented results with an operating model based on different assumptions. The impact of additional aspects and settings of the operating model, like fleet selectivity, implementation error, hyperstability/hyperdepletion of indices, the use of biannual indices, etc. should be explored. The relationship between the performance of SPiCT-based advice rules and tightening the prior on the shape parameter of the production curve ('n') has to be evaluated in more detail. As discussed earlier, this parameter is hard to estimate, but can be fixed or informed by a prior in data-limited cases. However, the prior affects the size of the confidence intervals of predicted stock status and thus the advice rules. Lastly, the performance for SPiCT and potential tuning options should be explored and evaluated with regard to stocks driven by recruitment-related instead of density-dependent processes, such as it is the case for short-lived species. In this regard, it would also be valuable to simulate stocks with an operating model with a finer temporal resolution such as quarterly or monthly time-steps. The introduced individual-based operating model (FLIBM) within the FLR framework poses a promising candidate for such simulation testing (see Section 4.4). Further investigating the performance on shorter time-scales than in this study. The risk/yield trade-offs on shorter time-scales can show slightly different patterns (cp. Figure 2.17) and are important because these depend on other stock characteristics and assumptions than those based on longer time-scales.

2.6 References

Beverton, R.J.H. and Holt, S.J. 1957. On the Dynamics of Exploited Fish Populations (Fisheries Investigations, Ser. 2, Vol. 19). UK Ministry of Agriculture and Fisheries, London.

Carruthers, T. R., and Hordyk, A. R. 2018a. DLMtool: Data-Limited Methods Toolkit. R package version 5.2.3. https://CRAN.R-project.org/package=DLMtool

Carruthers, T. R., and Hordyk, A. R. 2018b. The Data-Limited Methods Toolkit (DLM tool): An R package for informing management of data-limited populations. Methods in Ecology and Evolution.

Carruthers, T. R., and Hordyk, A. R. 2018c. Data-Limited Methods Toolkit (DLMtool 5.2).

Gislason, H., Daan, N., Rice, J. C., and Pope, J. G. 2010. Size, growth, temperature and the natural mortality of marine fish. Fish and Fisheries, 11(2), 149–158.

ICES. 2012. Report of the Workshop on the Development of Assessments based on LIFE History Traits and Exploitation Characteristics (WKLIFE).

ICES. 2013. Report of the Workshop on Guidelines for Management Strategy Evaluations (WKGMSE) , 21–23 January 2013, ICES HQ, Copenhagen, Denmark.

ICES. 2017a. Report of the Workshop on the Development of the ICES approach to providing MSY advice for category 3 and 4 stocks (WKMSYCat34), 6–10 March 2017, Copenhagen, Denmark. ICES CM 2017/ACOM:47. 53 pp.

ICES. 2017b. Report of the Working Group on Assessment of Demersal Stocks in the North Sea and Skagerrak (2017), 26 April–5 May 2017, ICES HQ. ICES CM 2017/ACOM:21. 1248 pp.

ICES. 2018a. ICES reference points for stocks in categories 3 and 4 In ICES Advisory Committee, 2018. ICES Advice 2018, Book 16, Section 16.4.3.2

ICES. 2018b. Report from the Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for stocks in categories 3–6, 2–6 October 2017, Lisbon, Portugal. ICES CM 2017/ACOM:43. 221 pp.

Jardim, E., Azevedo, M., and Brites, N. M. 2015. Harvest control rules for data limited stocks using length-based reference points and survey biomass indices. Fisheries research, 171, pp. 12–19.

Pella, J. J. and Tomlinson, P. K. 1969. A generalized stock production model. Bulletin of the Inter-American Tropical Tuna Commission, 13, 421–458.

Pedersen, M. W., and Berg, C. W. 2017. A stochastic surplus production model in continuous time. Fish and Fisheries, 18(2), 226–243.

Smith, A.D.M. 1994. Management strategy evaluation–The light on the hill. In: Population Dynamics for Fisheries Management, Australian Society for Fish Biology Workshop Proceedings, Perth 24–25 August 1993 (ed. D. A. Hancock). Australian Society for Fish Biology, Perth, pp. 249–253.

Thorson, J. T., Cope, J. M., Branch, T. A., and Jensen, O. P. 2012. Spawning biomass reference points for exploited marine fish, incorporating taxonomic and body size information. Canadian Journal of Fisheries and Aquatic Sciences, 69(9), 1556–1568.

Wang, S. P., Maunder, M. N., and Aires-da-Silva, A. 2014. Selectivity's distortion of the production function and its influence on management advice from surplus production models. Fisheries research, 158, 181–193.

2.7 Collated figures 2.13 through to 2.23

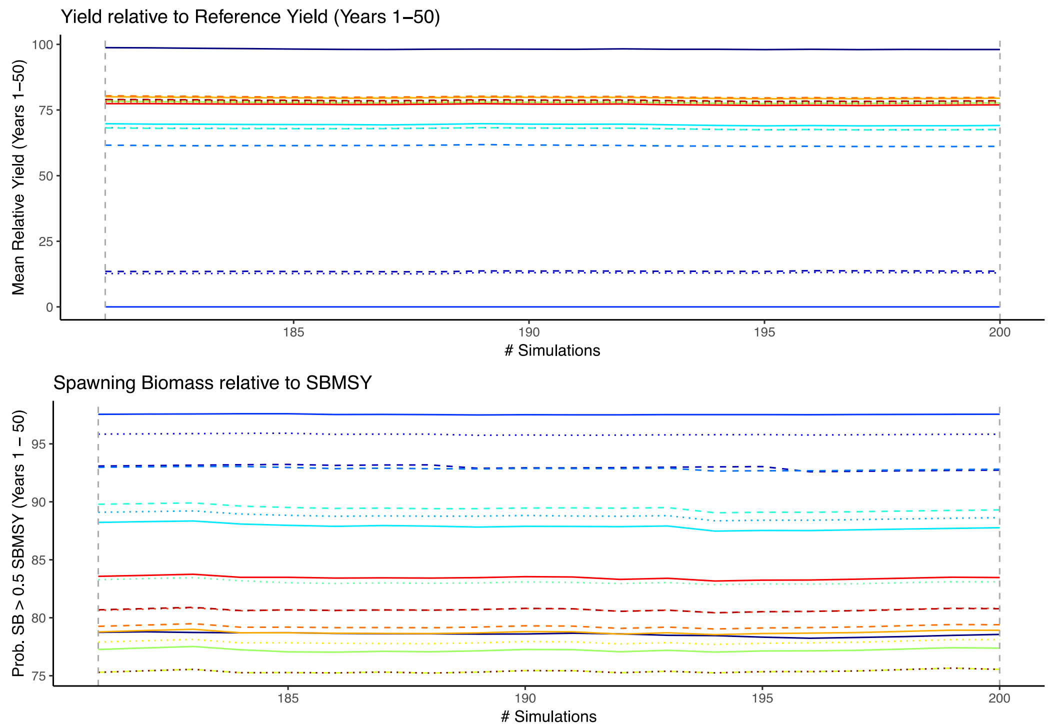


Figure 2.13. Mean relative yield and risk of falling below $B_{trigger}$ for different number of simulations for the anchovy stock and scenario 5. Colourful lines represent different advice rules. Levels are constant across tested number of simulations, indicating sufficiency of the number of simulations.

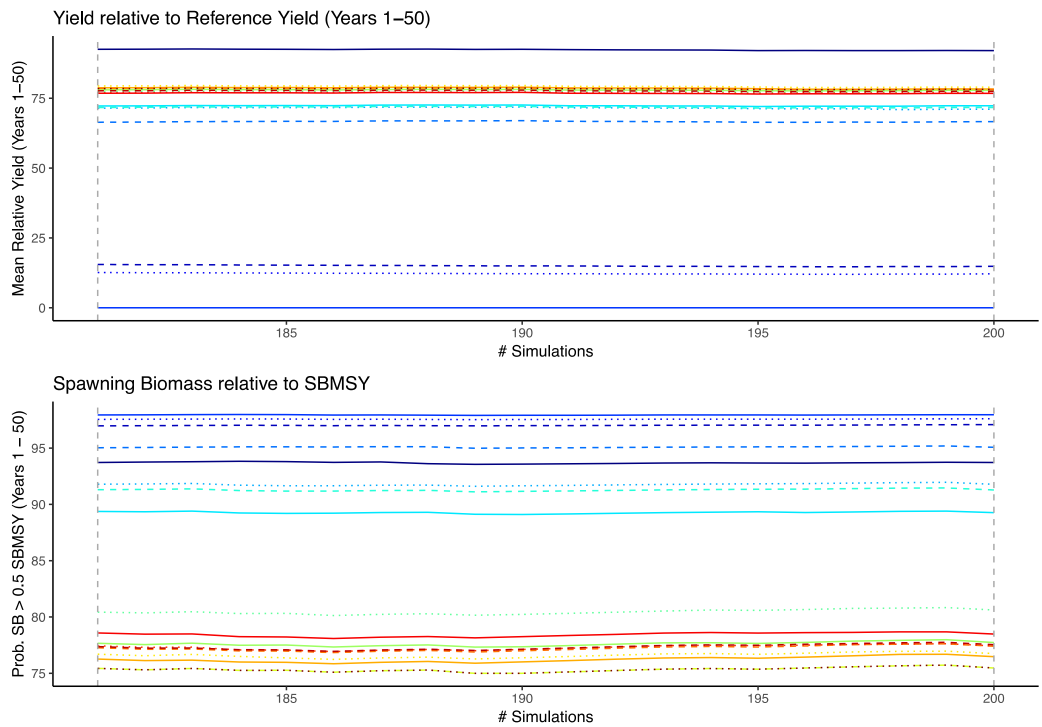


Figure 2.14. Mean relative yield and risk of falling below $B_{trigger}$ for different number of simulations for the haddock stock and scenario 5. Colourful lines represent different advice rules. Levels are constant across tested number of simulations, indicating sufficiency of the number of simulations.

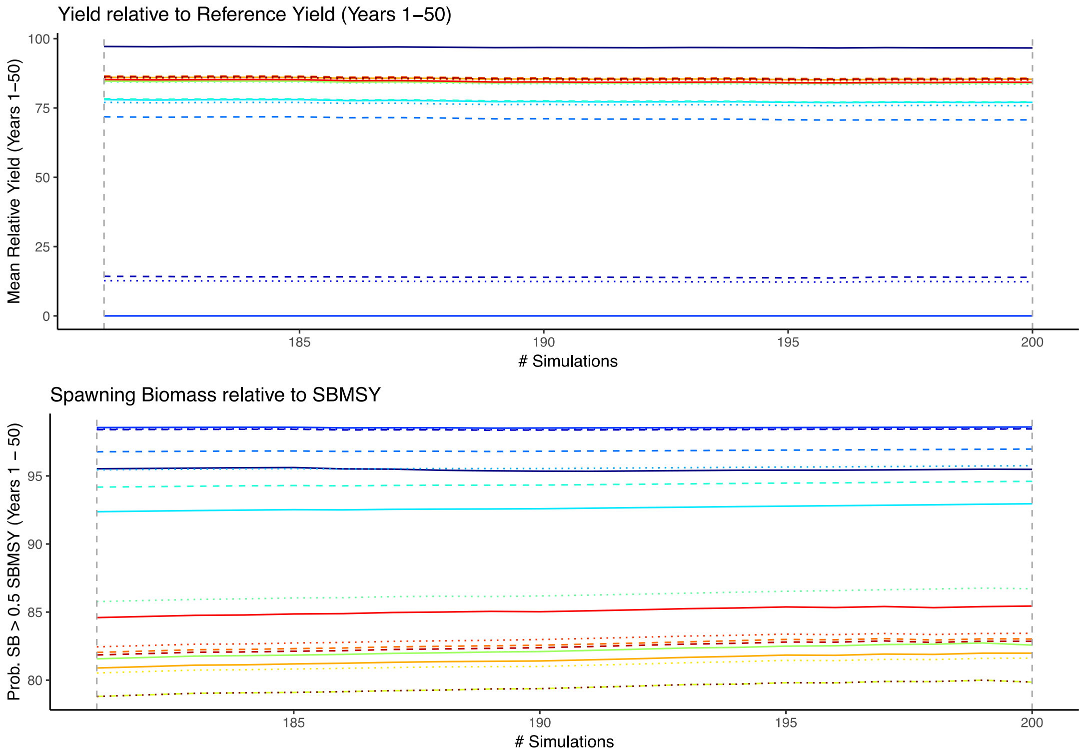


Figure 2.15. Mean relative yield and risk of falling below $B_{trigger}$ for different number of simulations for the ling stock and scenario 5. Colourful lines represent different advice rules. Levels are constant across tested number of simulations, indicating sufficiency of the number of simulations.

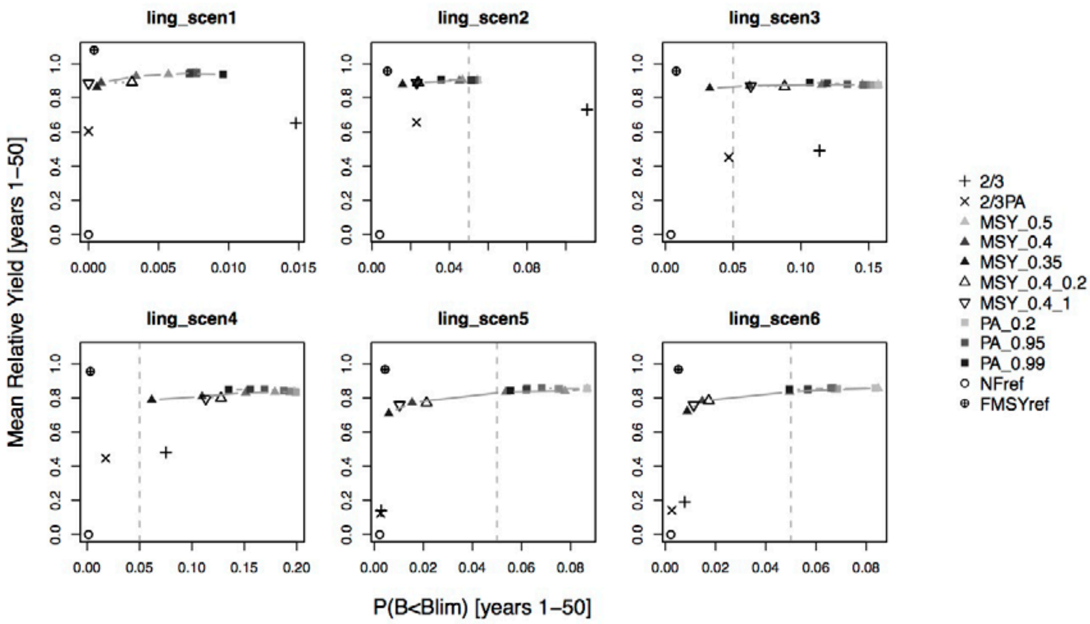


Figure 2.16. Trade-off graph of mean relative yield and risk 1 for ling over all projection years (1–50) and all scenarios with ⅔ and reference rules (NFref & FMSYref). Vertical dashed line represents the reference risk level of 5%. Solid lines between advice rules display the connection of common advice rules which only differ in the fractile or P_{PA}. Intermediate fractile levels not displayed in the legend can be found in Table 2.1.

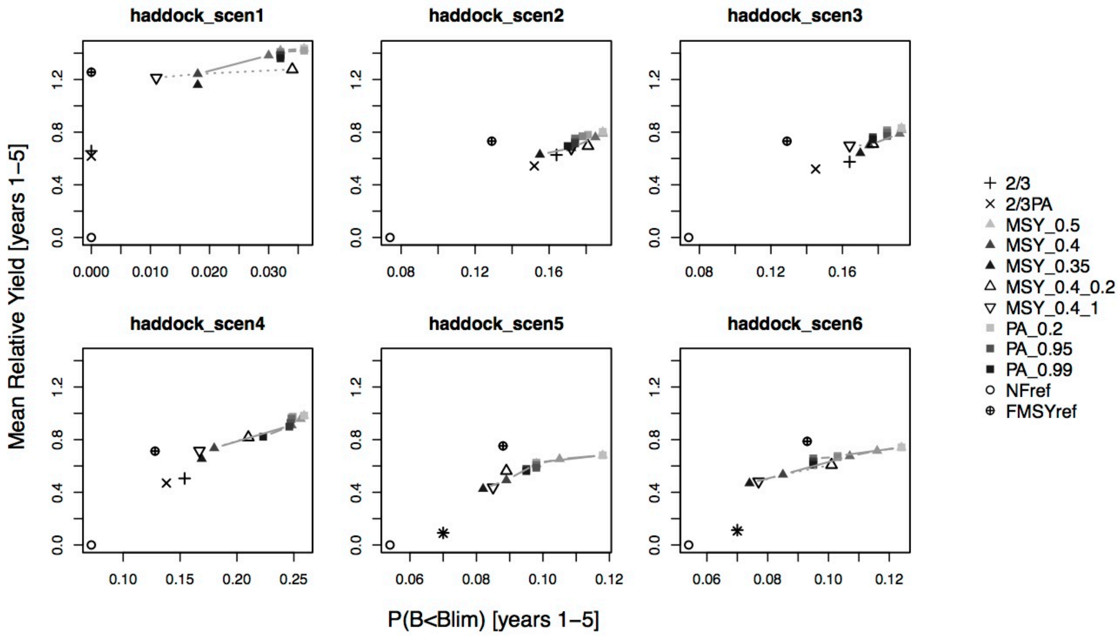


Figure 2.17. Trade-off graph of mean relative yield and risk 1 for haddock over first five years of projection period and all scenarios with ⅔ and reference rules (NFref & FMSYref). Vertical dashed line represents the reference risk level of 5%. Solid lines between advice rules display the connection of common advice rules which only differ in the fractile or P_{PA}. Intermediate fractile levels not displayed in the legend can be found in Table 2.1.

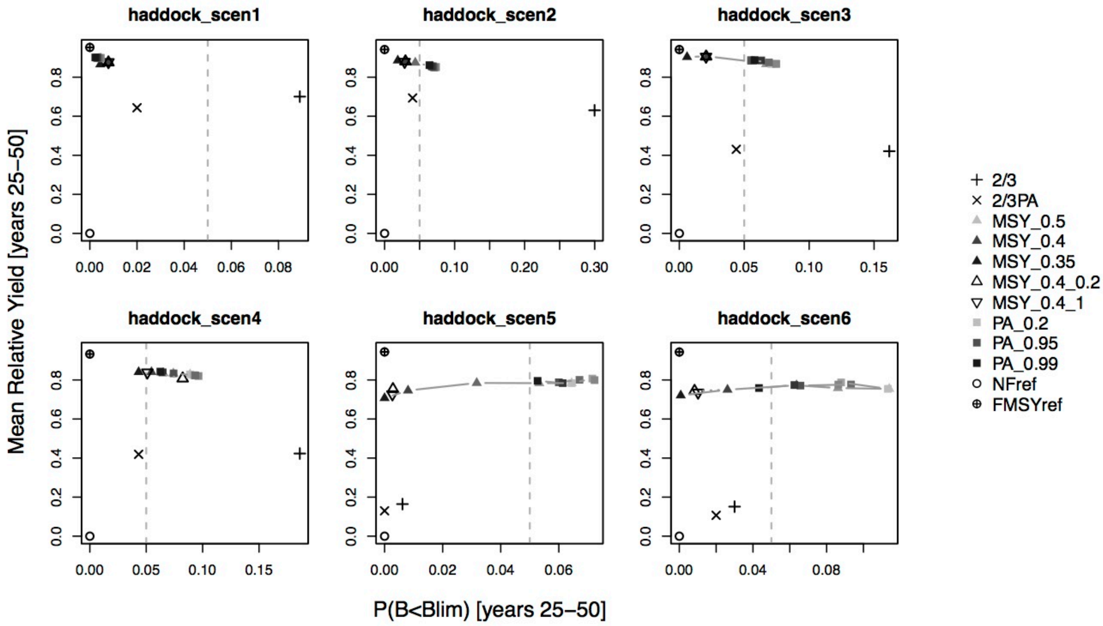


Figure 2.18. Trade-off graph of mean relative yield and risk 1 for haddock over last 25 years of projection period and all scenarios with ⅔ and reference rules (NFref & FMSYref). Vertical dashed line represents the reference risk level of 5%. Solid lines between advice rules display the connection of common advice rules which only differ in the fractile or P_{PA}. Intermediate fractile levels not displayed in the legend can be found in Table 2.1.

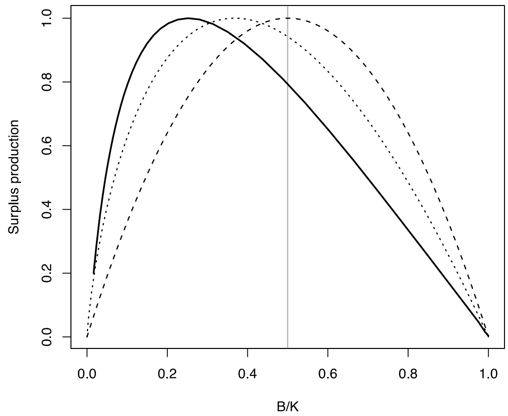


Figure 2.19. Theoretical production curve of the haddock stock. Grey vertical line and dashed curve indicate B/K level and shape of the production curve of the Schaefer model (n=2), while dotted curve represents the production curve for the Fox model (n=1). Right-skewed production curve of haddock indicates a value for n < 1.

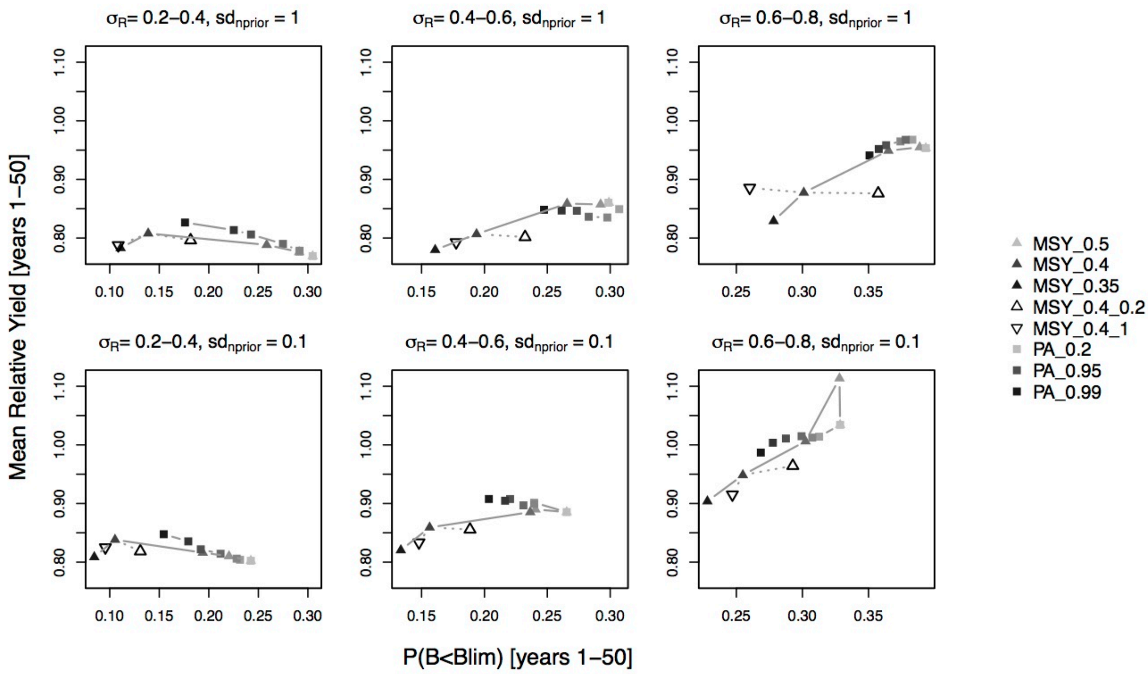


Figure 2.20. Trade-off graph of mean relative yield and risk 1 for anchovy over all projection years (1–50) for three levels of recruitment variability (σ_R; columns) each with two different priors for the shape parameter of the production curve (rows). Based on the anchovy stock and scenario 4. Vertical dashed line represents the reference risk level of 5%. Solid lines between advice rules display the connection of common advice rules which only differ in the fractile or P_{PA}. Intermediate fractile levels not displayed in the legend can be found in Table 2.1.

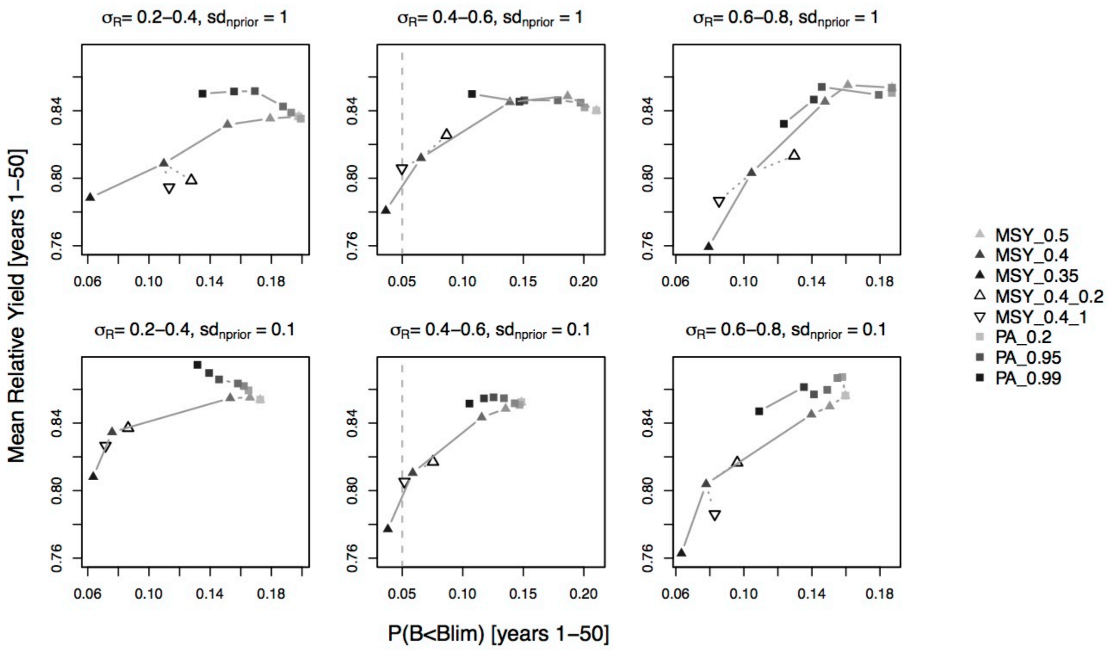


Figure 2.21. Trade-off graph of mean relative yield and risk 1 for ling over all projection years (1–50) for three levels of recruitment variability (σ_R; columns) each with two different priors for the shape parameter of the production curve (rows). Based on the ling stock and scenario 4. Vertical dashed line represents the reference risk level of 5%. Solid lines between advice rules display the connection of common advice rules which only differ in the fractile or P_{PA}. Intermediate fractile levels not displayed in the legend can be found in Table 2.1.

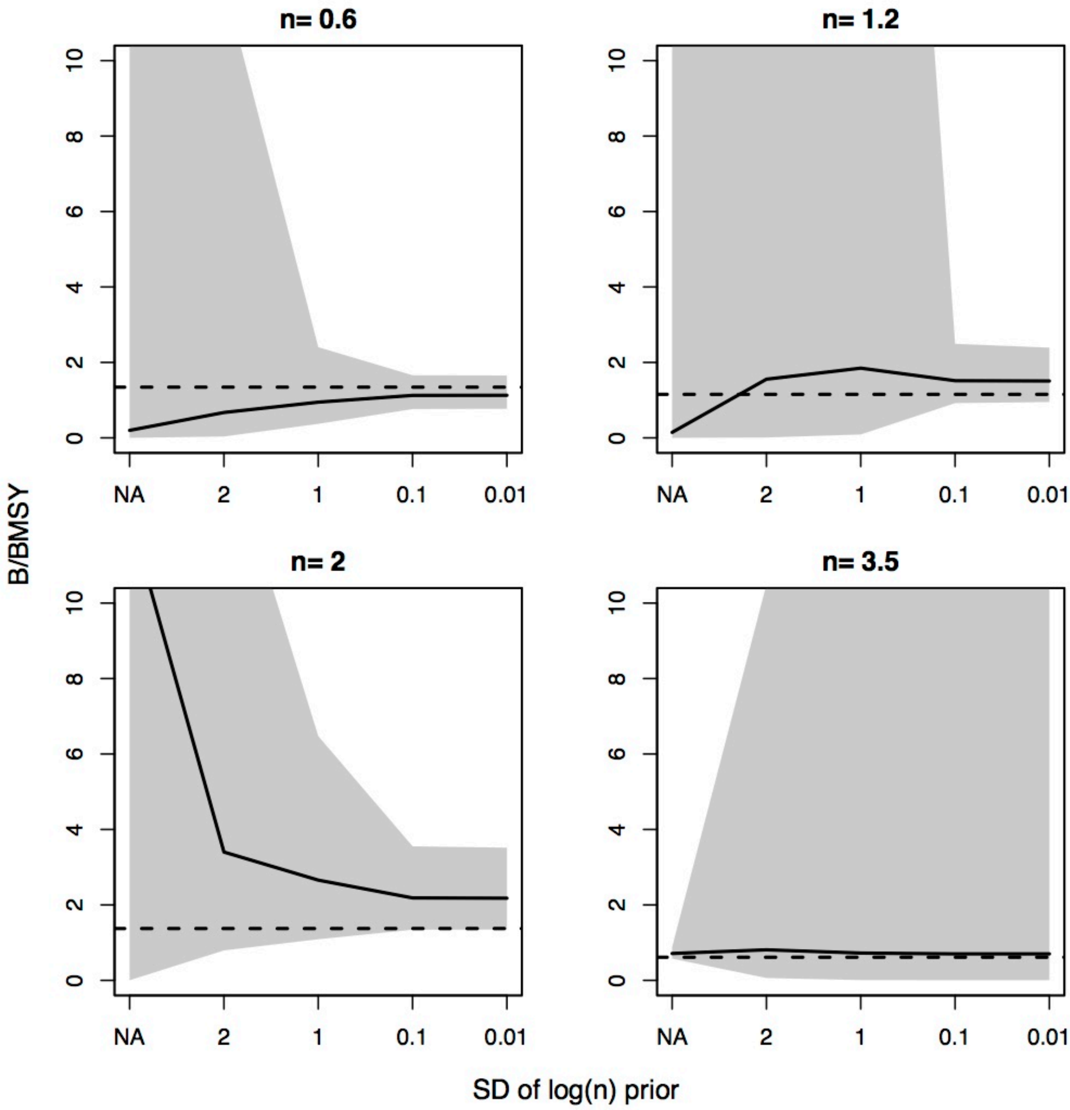


Figure 2.22. Relative biomass (B/B_{MSY}) for different priors for all simulated stocks. Shaded areas represent 95% confidence intervals and dashed horizontal line represents true B/B_{MSY} level.

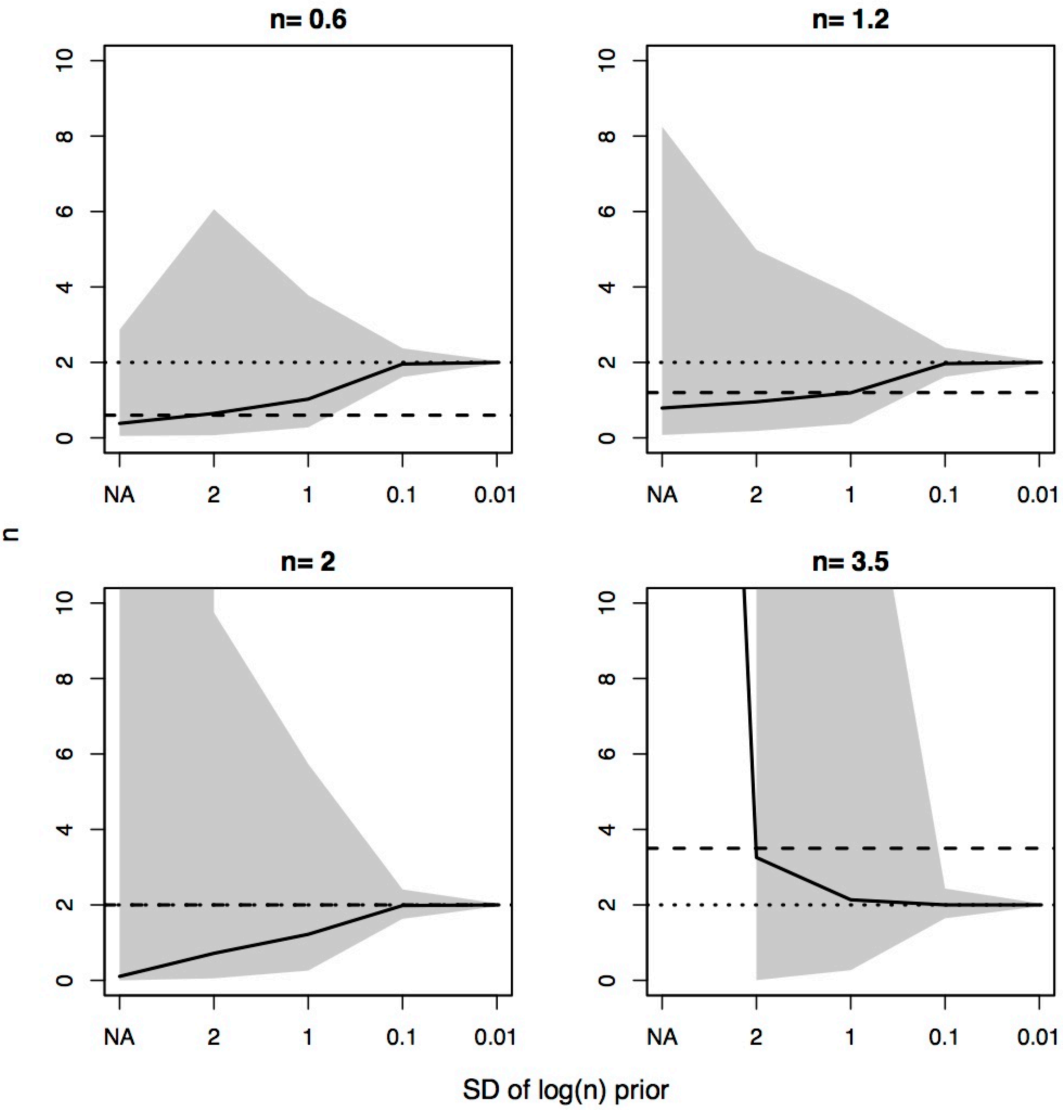


Figure 2.23. Estimated shape parameter n against different priors for all simulated stocks. Shaded areas represent 95% confidence intervals and dashed horizontal line represents true value of n.

3 MSE testing of WKMSYCat34 catch rules in FLR and linking the performance to life-history traits

3.1 Work of the subgroup during the workshop

This Section provides a high-level summary, of the work presented and discussed in the subgroup. Attached to this report is a working document which describes the analysis in detail (Annex 2).

The analysis presented in the WKLIFE VII report (ICES, 2018) was limited by the number of stocks considered (only four representative stocks for the detailed analysis), and showed some promise in linking performance of the catch rules to life-history traits (using the ratio between natural mortality and growth rate, *M/k*). The work presented here extends the analysis to 29 stocks, and explicitly deals with the link between performance of the catch rules and life-history traits. The extension to 29 stocks of varying life-history parameters increases the opportunity to generalise conclusions. A penalised regression technique was used to investigate which of the life-history parameters were most influential on six key performance statistics. This analysis found that the von Bertalanffy growth parameter *k* was the most influential on the performance of WKMSYCat34 catch rule 3.2.1 (ICES, 2017).

Subsequently, a cluster analysis was performed using the median of the SSB time-series relative to B_{MSY} for the 29 stocks (Figure 3.1). If only two clusters were considered, these correspond to one cluster with *k* at or above 0.38 (stocks that collapsed) and another with *k* at or below 0.32 (stocks that survived). The general conclusion with regard to *k* is that catch rule 3.2.1 should not be used for stocks with $k > 0.32$.

An analysis of tuning with a multiplier applied to catch rule 3.2.1 indicated a trade-off between improved risk and loss of yield within each cluster, and stocks ended up overshooting B_{MSY} by some margin (even for multipliers below, but still close to 1, Figure 3.2). If a general multiplier was needed for stocks with $k \leq 0.32$, then a multiplier of no more than 0.8 would ensure the risk of falling below B_{lim} would not exceed 5%. If a multiplier was applied based on more detailed information about *k*, then for stocks with *k* in the range 0.08–0.19, a multiplier of 0.8–0.85 (i.e. no more than 0.85) would be needed and for stocks with *k* in the range of 0.20–0.32, a multiplier of 0.8–0.9 (i.e. no more than 0.9) would be needed in order to ensure the risk of falling below B_{lim} would not exceed 5% in both cases (Figure 3.3). These values are conditional on the assumptions of the simulation study.

The performance could be improved somewhat with an upper TAC constraint of 1.2 (+20% change) in combination with a lower TAC constraint of 0.7 (-30% change).

When the catch rule was implemented without uncertainty and reference points were based on MSY, then most stocks (with $k \leq 0.32$) approached B_{MSY} (Figure 3.4).

Using more recent data also improved the performance (Figure 3.5).

An alternative catch rule tested was WKMSYCat34 catch rule 3.2.2 and this catch rule performed well for stocks with $k \leq 0.32$ if the MSY proxy harvest rate was known. The suitable range of *k* values could be extended by using more recent data (Figure 3.6).

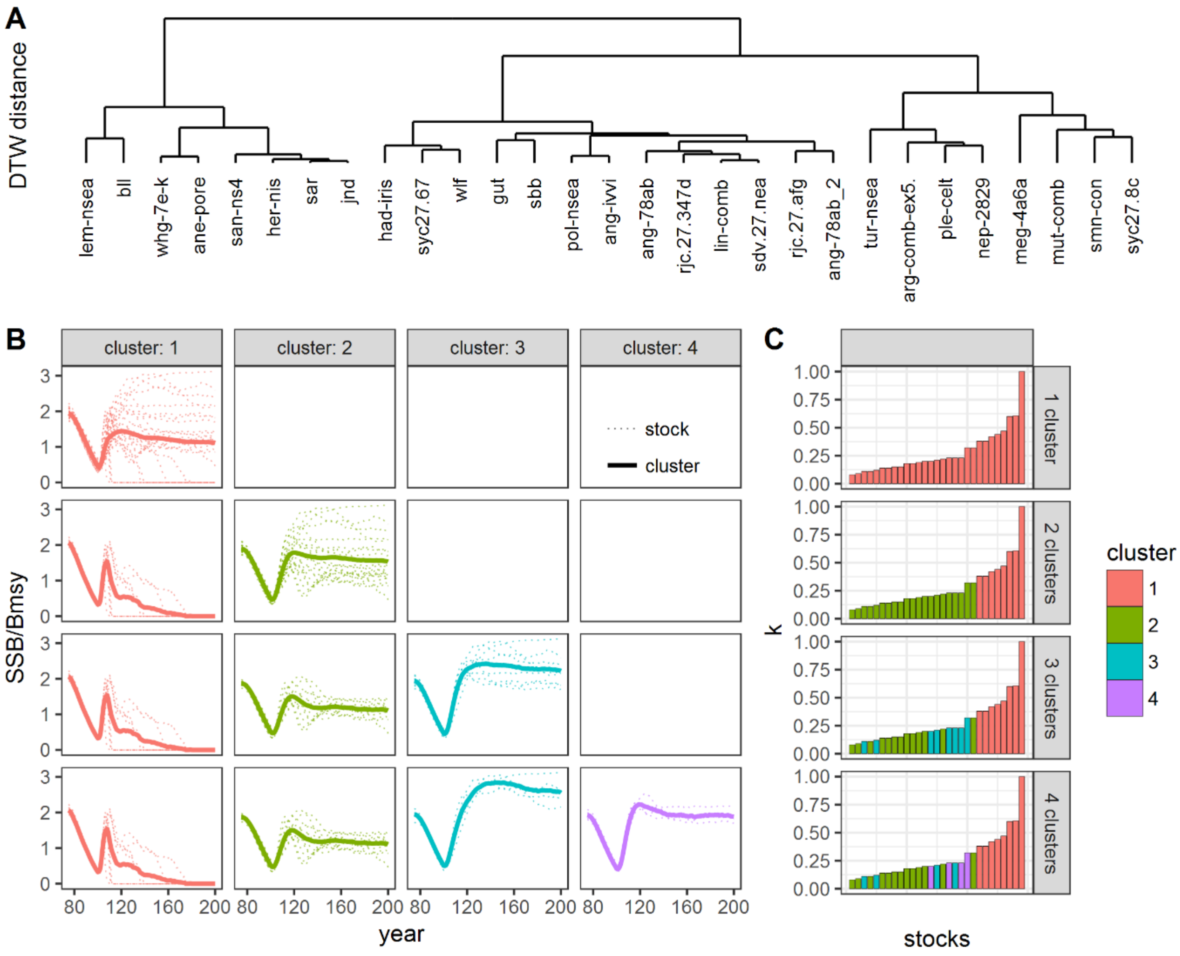


Figure 3.1. Results of the hierarchical clustering approach of relative SSB time-series from the simulations of catch rule 3.2.1 and the one-way fishing history. A shows a dendrogram of the time-series for the 29 simulated stocks. The y-axis corresponds to the dynamic time warping (DTW) distance between the time-series. B represents the median SSB time-series for all stocks (dotted lines) and the centroids (solid bold line). Rows represent the number of clusters and each column is one cluster. C shows von Bertalanffy *k* values for all stocks, sorted in ascending order and colour-coded for the clusters shown in B.

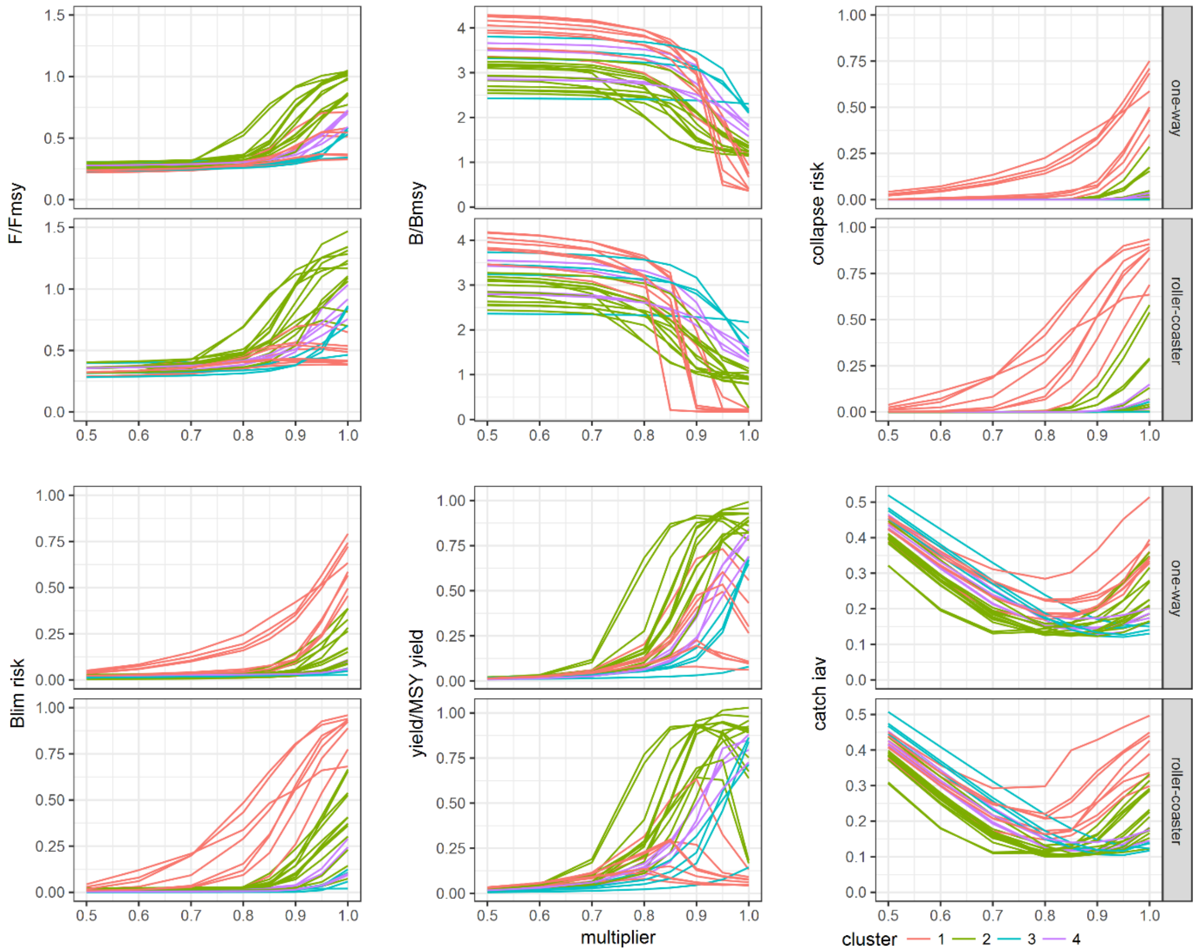


Figure 3.2. Effect of implementing a multiplier on the performance of catch rule 3.2.1. The clusters correspond to the ones defined in Figure 3.1.

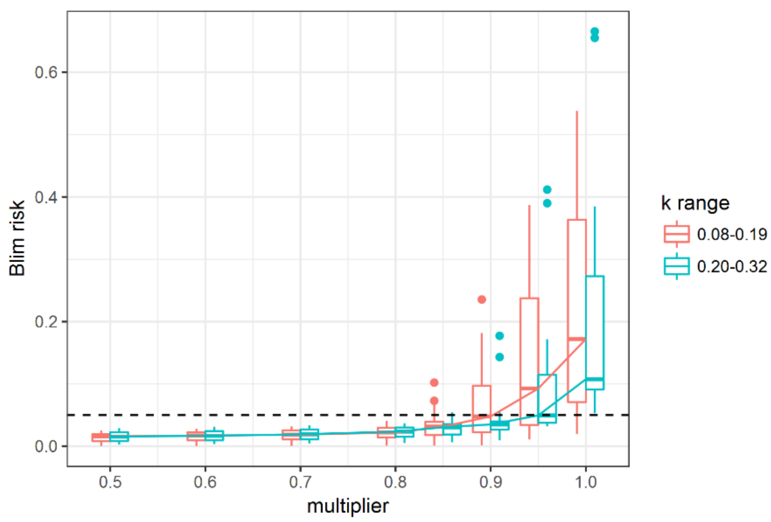


Figure 3.3. B_{lim} risk for the stocks in clusters 2–4, split into two groups depending on k. The boxplots show the range of risk for the stocks combined for the two fishing histories for a given multiplier and the solid line the median. The black dashed line indicates the 5% probability.

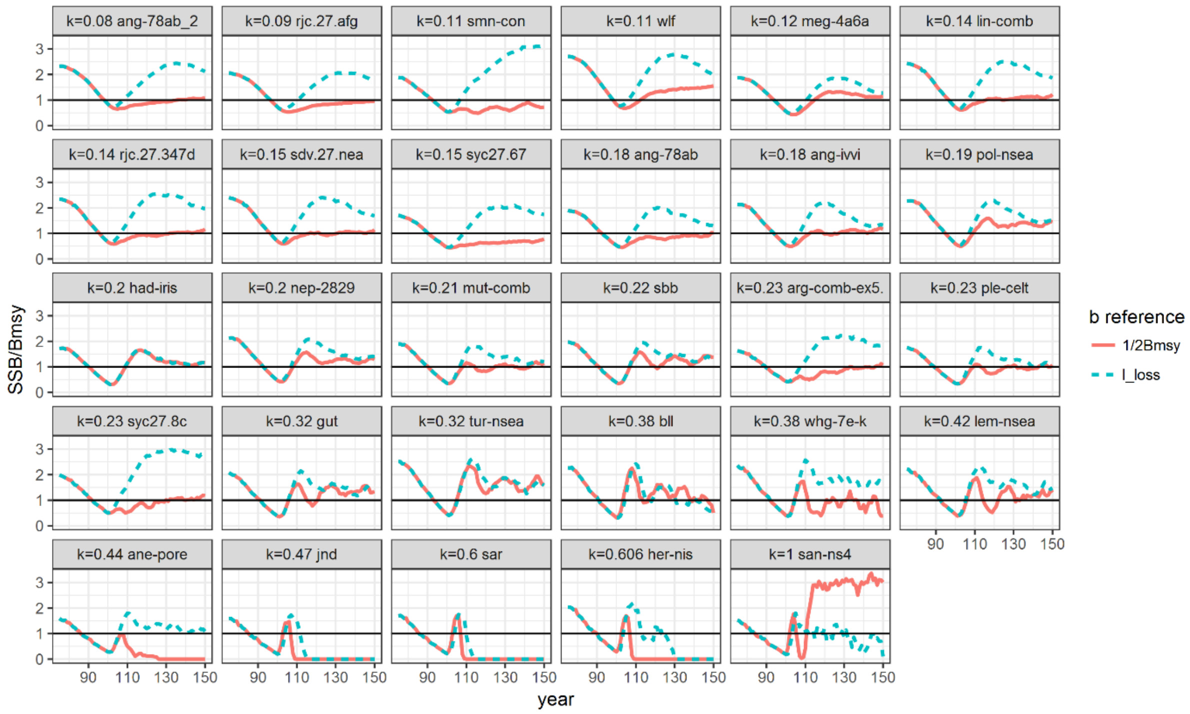


Figure 3.4. SSB trajectories from catch rule 3.2.1 with perfect information and knowledge (red solid line) compared with the scenarios where $I_{trigger}$ is set to the lowest observed index value (blue dashed line). Shown are the medians for all simulated stocks with the one-way fishing history.

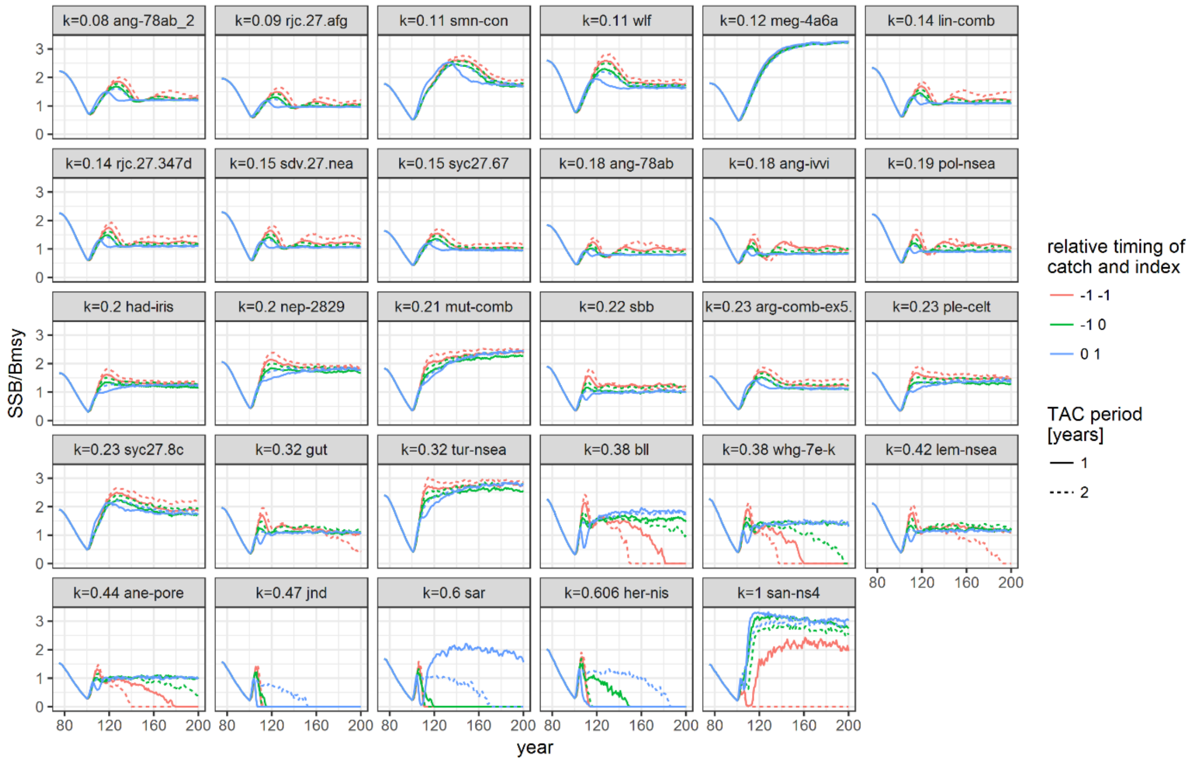


Figure 3.5. Effect of data timing used in the catch rule on the biomass trajectory for the 29 simulated stocks, sorted by k. The values for the timing of catch and index are relative to the intermediate (assessment) year (0), -1 stands for the year before the intermediate year and 1 for the (first) advice year. TAC period 2 refers to biennial advice, and 1 to annual advice.

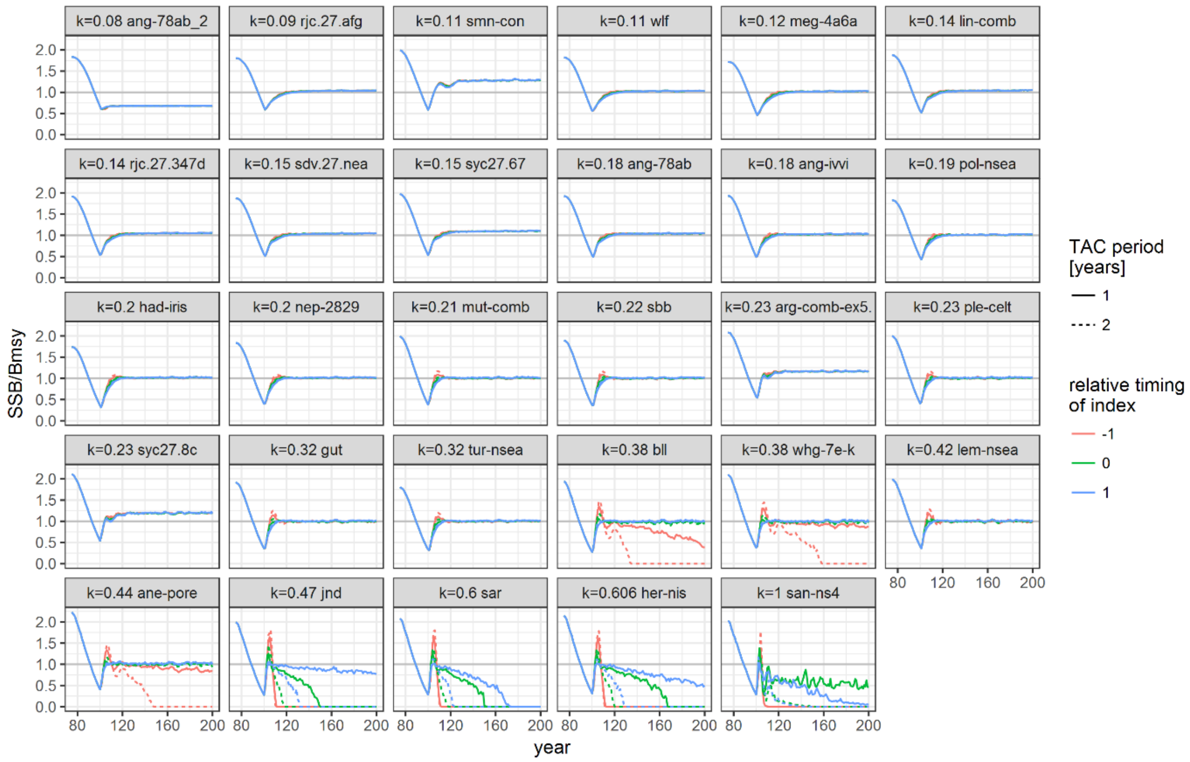


Figure 3.6. Effect of data timing on the performance of the alternative catch rule 3.2.2. Shown are the median SSB trajectories for the 29 simulated stocks, ordered by k, for the roller-coaster fishing history and for the case where F_{proxy} was derived from F_{MSY}. The timing of the index is relative the intermediate (assessment) year, -1 indicates data up to the year before intermediate year and 1 up to the beginning of the advice for which the advice is given. TAC period 2 refers to biennial advice, and 1 to annual advice.

3.2 Conclusions

1) The WKMSYCat34 catch rule 3.2.1 suffers from a range of issues, as has been previously described in detail, e.g. time-lags between assessment and advice, assumed values for reference points and/or period, and the catch rule being a product of several factors; WKLIFE VII (ICES, 2018).

2) Under Gislason mortality and sigmaR=0.3, and with the usual lags (2 over 3 rule and the lag between assessment and advice), the 3.2.1 catch rule without further tuning resulted in collapses for stocks with k>0.32, and three further clusters were identified for the cases where k≤0.32, those that end around B_{MSY}, around 2B_{MSY}, and around 3B_{MSY}:

2.1) Adding a multiplier to the catch rule (0.5–0.95) without weighting the different components of the rule did not lead to improvement across all summary statistics (i.e. generally there was a catch vs. risk trade-off).

2.2) Performance was improved by introducing asymmetric i.e. upper (~1.2) and lower (~0.7) catch constraints.

2.3) Performance was improved by reducing time-lags (i.e. using more recent data), even for some of the k>0.32 stocks; reducing time-lags also and generally reducing fluctuations.

3) Similar conclusions apply for the 3.2.2 catch rule (the *Icelandic* rule) in terms of the clusters based on *k*, and the improvement in performance by reducing time-lags.

4) For both rules 3.2.1 and 3.2.2, the extent to which reference levels were *correctly* set determined how precautionary the rules were.

5) Recruitment variability (*sigmaR*) and alternative natural mortality (*M*) assumptions had an important impact on outcomes since these affect the nature of the variability of the time-series.

  5.1) the *k* above which the 3.2.1 catch rule failed was reduced for some combinations of *sigmaR* and *M*, and the extent of the reduction also depended on operating model scenario (one-way or roller-coaster);

  5.2) the use of alternative *M* vectors changed the nature of the time-series (e.g. increased fluctuations for higher *M*), and hence the performance of the 3.2.1 catch rule.

6) When running simulations under a perfect information scenario (setting $I_{trigger}$ to $0.5B_{MSY}$ and using the MSY length as reference length) the catch rule moved most stocks (apart from the high *k* stocks) towards B_{MSY} and maintained this level, i.e. the catch rule led to the desired results. A further analysis of the individual catch components under perfect knowledge conditions revealed that:

  6.1) the *r* and *b* components of the rule dominated at different times, i.e. between the recovery period and maintaining the stock at the MSY level. The *f* component had the lowest impact; this highlighted the need to consider the relative weighting of these different components, and that different weighting combinations could be used to improve performance of the rule;

  6.2) the clustering when $k<0.32$ was likely due to the way the protection element of the rule (the *b*-component) specified the $I_{trigger}$ value; when this value was set at $0.5B_{MSY}$ instead of 1.4 times the lowest observed historical index, the rules for $k<0.32$ reached their intended target; a reason for this is that the oscillations observed in the stock dynamics increased with *k*, and the very high volatility of the highest *k* stocks might be used to explain the poor performance of the catch rule for these stocks.

3.3 Recommendation

The performance of the 3.2.1 catch rule can be improved in terms of risk by applying a multiplier. Last year, based on a limited number of simulations (only four representative stocks), a multiplier of 0.95 was proposed independent of *k*. This year, to keep the probability of dropping below B_{lim} to 5% or less, and based on a larger number of stocks representing a wide range of life-history characteristics, simulations indicated a revision of this proposal incorporating *k*. If a multiplier were to be used independent of *k*, a multiplier of no greater than 0.8 is recommended. If a multiplier were to be used depending on the value of *k*, then for *k* values in the range of 0.08–0.19, a multiplier of no greater than 0.85 is recommended, and for *k* values in the range of 0.20–0.32, a multiplier of no greater than 0.90 is recommended. For *k* values above 0.32, the 3.2.1 catch rule should not be applied in its current form.

3.4 Future directions

Trends and fluctuations in populations are determined by complex interactions between extrinsic forcing and intrinsic dynamics. For example, stochastic recruitment can induce low-frequency variability, i.e. 'cohort resonance', which can induce apparent trends in abundance and may be common in age-structured populations; such low-frequency fluctuations can potentially mimic or cloak critical variation in abundance linked to environmental change, over-exploitation or other types of anthropogenic forcing (Bjørnstad, 2004). Although important, these effects can be difficult to disentangle. The simulations so far show that life histories are important and should be used to help condition operating models to ensure robust feedback-control rules. MSE is important to help develop these robust feedback control rules and to help identify appropriate observational systems.

Although the performance of the HCR depended on the life-history characteristic, it was not in the way initially expected, i.e. the outcomes could not be grouped solely by whether the Operating Models (OMs) represented fast growing vs. late maturing species or demersal vs. pelagic stocks. What was important was the nature of the dynamics, i.e. how variable was the stock between years; for example, a stock could exhibit high interannual variability if natural mortality and recruitment variability was high, regardless of the values of k, L_{inf}, L_{50}. The nature of the indices is also important; for example, even if a stock had low interannual variability, an index could be highly variable if it was based on juveniles or there were large changes in spatial distribution between years. It is therefore necessary to look at the robustness of HCRs to the nature of the time-series of the stock (as represented by the OM) and to the characteristics of the data collected from it (as represented by the Observation Error Model). This will require tuning by constructing a reference set of OMs and then tuning the HCR to secure the desired trade-offs. The work so far can be considered as focusing first on developing HCR that perform satisfactorily for a reference set, the next step is to develop case-specific HCRs.

1) Aspects to consider for the 3.2.1 rule by the next meeting would be:
   - 1.1) Investigating the impact of relative weighting of the *r*, *f* and *b* components of the rule on the performance of the rule;
   - 1.2) Investigating more extensively the time-lag properties of the *r* component, including alternative formulations;
   - 1.3) Setting of appropriate reference levels in the *f* and *b* component of the rules, and the extent to which this could be done with tuning that depends on life-history traits and/or the nature of the time-series;
   - 1.4) Investigation of the use of trends in an index without a reference level.

2) Longer term aspect to consider for data-limited rules:
   - 2.1) Focusing on the nature of time-series and developing diagnostics that could help determine the rules that would work well under alternative characterisations of the nature of the time-series, and aspects such as quality of data used by the rules (and hence ability to detect signals), ability to set appropriate reference points, etc.;
   - 2.2) Linking life-history traits, the form of density-dependence and fishery characteristics (e.g. including fishery selectivity) to the nature of resulting time-series;
   - 2.3) Develop guidance for use of catch rules by linking (a) and (b);

2.4) Avoiding the shot-gun approach to simulation testing e.g. by making more extensive use of sensitivity (elasticity) analysis to highlight factors that are most important in determining the time-series behaviour of stocks;

2.5) Investigating the implications of how the operating models are set up (fishing history, depletion levels, selectivity assumptions, mortality) on the behaviour of the stock and on the performance of the catch rule.

3.5 References

Bjørnstad, O. N., Nisbet, R. M., and Fromentin, J. M. 2004. Trends and cohort resonant effects in age-structured populations. Journal of animal ecology, 73(6), 1157–1167.

ICES.2017. Report of the Workshop on the Development of the ICES approach to providing MSY advice for category 3 and 4 stocks (WKMSYCat34), 6–10 March 2017, Copenhagen, Denmark. ICES CM 2017/ ACOM:47. 53 pp.

ICES. 2018. Report of the ICES Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for stocks in categories 3–6 (WKLIFE VII), 2–6 October 2017, Lisbon, Portugal. ICES CM 2016/ACOM:59. 106 pp.

4 Short-lived species

4.1 Performance of HCRs for in-year advice based on survey trends

The development of management advice rules for Data-limited stocks was driven basically by long-living stocks having little InterAnnual Variability (IAV), and where observation errors in the survey indices can be wider than IAV. For this reason, Uncertainty Cap constrains were set up to avoid noisy inputs from surveys. Furthermore, most of the Rules proposed for category 3 stock to give trend advice based on surveys (methods 3.2 and 3.3) were devised to encapsulate trends from recent past (until year Y-1) to provide advice for year Y+1 (ICES, 2012) (assuming changes happen slowly for these stocks).

WKMSYCat34 (ICES, 2017) expanded those methods to accommodate for various assessments of F_{proxy} and to include some threshold Index values below which a decrease of allowable catches would be imposed, as reflected in method 3.2.1.1. Such F_{proxy} might come from either a surplus production model (as SPICT) or from a length-based indicator of exploitation status.

However, short-lived species have particular features that require different formulation of the DLS than the originally formulated methods 3.2 and 3.3 (in ICES, 2012), or the expanded versions in WKMSYCat34 (ICES, 2017 for the following reasons:

- Sometimes surplus production model do not encapsulate the dynamics of these populations and usually length-based indicators of exploitations status are not valid for such variable resources for which length distribution almost entirely depends on the strength of the most recent year class;
- Furthermore, direct monitoring systems by surveys can results in observation errors smaller than IAV of the populations, and could make unnecessary (or risky) the application of the typical 20% uncertainty cap for such highly fluctuating populations;
- Finally, the huge IAV suggest that recent past changes in the population are not probably applicable to the next future changes in the population (as implied in the classical applications of the methods 3). This calls for adaptive in-year advice where the most recent information on the current status of the population is used to manage the population for a management year starting just one or two months after the survey information is made available (based on trend based advices). This procedure reduces the typical 1 year gap between base information, advice and management, and it makes the management being actually informed on almost all age classes contributing to the catches and the SSB of the managed year, reducing thus the uncertainty associated to the advice. This reduction of uncertainty may call again for a reduction of the uncertainty cap constrains.

A WD presented to WKLIFE (Uriarte *et al*., Annex 3) assessed the performance of in-year trend based advice using modified DLS methods 3.2 and 3.3 for short-lived stocks, subject to several interannual uncertainty cap levels, with application to anchovy in 9a South.

In particular the following formulations were tested:

- Method 3.2, Trend-based methods of the types one-over-Nyears or two-over-N year or three-over-Nyears rule (for N going from 1 to 3) (methods

3.2). All of them are adapted for in-year advices in the form Tx/z appearing below:

$$C_{y+1} = C_y \frac{\sum_{y-x}^{y} I_i/(x+1)}{\sum_{y-z}^{y-x-1} I_i/(z-x)} \qquad \text{Equation 4.1.1}$$

These are blind rules where the actual harvest rates will be changing gradually in time according to the indicators of the current situation of the stock compared to the past indices. The two over three and three over five trend-based advices are compared with the one over two and one over three advices. This trend-based rules will be called as $T^1/_2$, $T^1/_3$, $T^2/_3$ and $T^3/_5$ respectively with the quotients referring to the numbers of years in the numerator and denominator respectively.

- Method 3.3, Harvest rate methods (or F_{proxy}): where past harvest rates were assumed to be sustainable. In particular, the range of years over which the F_{proxy} was obtained estimated was the starting 20 years simulated population period subject to a selected predefined sustainable harvest rate. So the mean of the harvest rate over the starting population (MeanStHr) is the F_{proxy} which will be applied over the 20 year management period. The generic formula appears below for N years between z and x in the prior period:

$$C_{y+1} = I_y \frac{\sum_{y-z}^{y-x} C_i/(z-x)}{\sum_{y-z}^{y-x} I_i/(z-x)} \qquad \text{Equation 4.1.2}$$

But it was applied only for the particular case of N (20 = z-x. unchanged for the initial unmanaged period of the fishery).

Effect of the Uncertainty cap on the performance of those rules were tested for 20% , 50% and 80% uncertainty cap levels (UC) and unconstrained (termed here as the 100%) versions of the former rules.

The general objective of the exercise was to test whether for in-year advice the one-over-two or one-over-three methods outperform the other rules two-over-three or three-over-five, and at the same time to assess whether the uncertainty cap of 20% is advisable or if a weaker or none uncertainty cap should be selected for these advisory rules for in-year advice. These questions are addressed in terms of the ratio of the observation errors of the surveys in relation to the Interannual Variability of the population (IAV). The IAV here was taken as the Interannual variance of biomass between consecutive years (in log scale) in the time-series (without exploitation).

Method

The population is age structured (0–6+) which is moved forward on half-year basis.

A 250 simulations of managed populations for 20 years were run for each Harvest control rules defined by the different methods 3.2 and the Method 3.5 (HR(20)) and for the different uncertainty Cap ranges. They all are preceded by 20 years of a (randomly) exploited unmanaged population for two scenarios of initial harvest levels: either to a well below F_{MSY} (about half) or just below the maximum sustainably fishing mortality values (F_{MSY} as deduced from deterministic F_{MSY} estimations) (with a random log scaled variability of 0.2). The initial population is used as reference of a sustainable starting population. Hence performance of the harvest control rules are tested against trends in

SSB, F or Hr and probabilities of exceeding past harvest rates or lowest SSB in the starting unmanaged population (taking this a B_{loss}=B_{lim}). The MSE Simulations are run in an Excel Workbook with VBA macros (etc. see further detains in the attached WD).

The dynamics of the simulated population was that defining the anchovy in 9a South as resulting from last assessment in WGHANSA 2018. A hockey-stick defined by an inflection SSB point at 1440 t with a geometric mean recruitment above that level of 1632 million age 0 fish is assumed, subject to a log Sigma yearly realization of 0.471.

It is assumed that a single survey is available having a partial catchability at age 1 (around 0.7 for the anchovy 9a) and a common catchability for all ages 2+ (of 1), being subject to a random yearly observation error affecting equally all ages. The simulation test the effect of different log observation errors relative to the IAV ranging from a half (½), the same (1) and two (2) times the IAV of this population (which is equal to IAV= 0.347) and an additional typical 0.25 log sigma Observation error.

For the in-year advice it is assumed the survey assess age 1+ in the first half of year y to provide indication of population biomass of ages1+ (not necessarily equal to SSB) to serve as source of advice for a management for the second half of year y and first half of year y+1 (from July Y to Y+1, called in the formulas above as management year Y+1).

The 5 HCR * 4 Uncertainty Cap levels * 2 starting differently harvested Populations * 4 survey observation errors make a total of 160 management testing exercises of 250 simulations each.

Results

Summary results for the initial population being harvested around a harvest rate on SSB of 0.6 (just below deterministic F_{MSY}) are presented below, while that being harvest around half deterministic F_{MSY} is included only in the attached WD (Uriarte *et al*. WD).

Figure 4.1.1 compares the SSB trajectories of the anchovy 9a population subject to in-year advice with HCRules T($^2/_3$) and T($^1/_2$) for the typical 0.25 log observation error of surveys (i.e. at 0.7 times IAV). In all cases the starting population declines over the 20 years prior to the start of the managed period. And in all cases management with both HCRs leads to a gradual recovery of the population (mean values). Recovery is more pronounced in the case of HCR T($^1/_2$) with 80% uncertainty Cap, followed the 50% and none uncertainty cap level (referred in the graph as 100%).

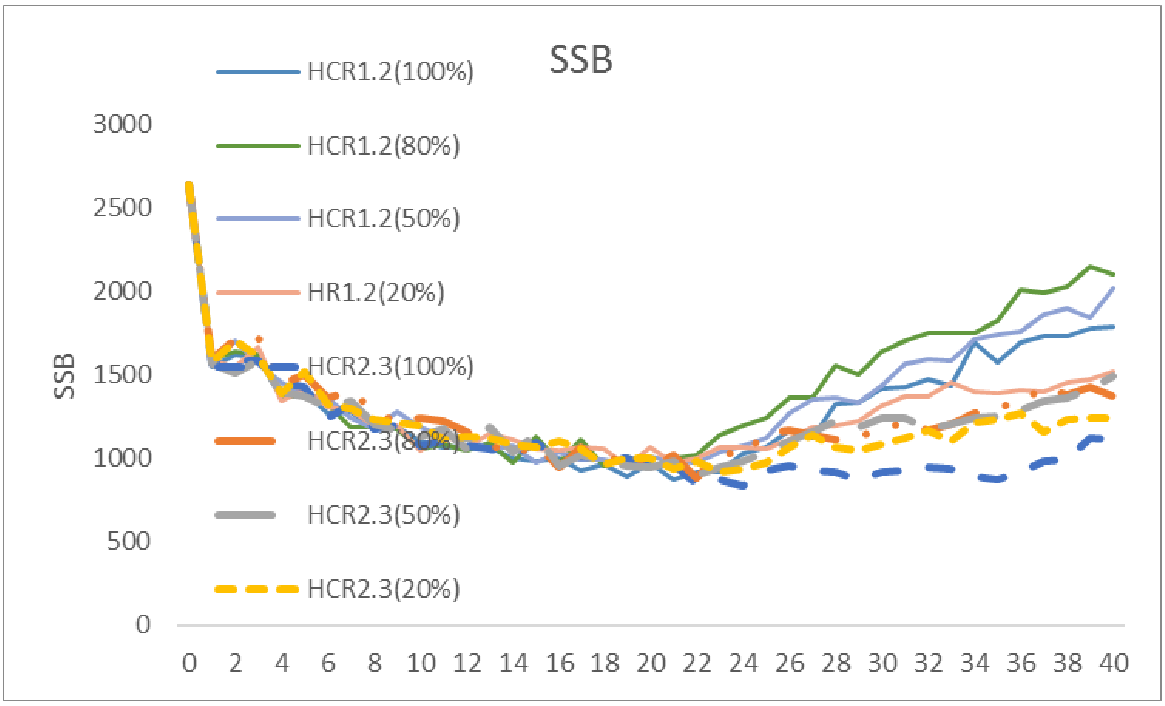


Figure 4.3.1. SSB trajectories of managed populations for the HCRules T(2/3) and T(1/2) for the typical 0.25 log observation error of surveys (i.e. at 0.7 times IAV) for different Uncertainty Cap levels (in brackets from 20% to 100% -the latter meaning no uncertainty cap applies). The first 20 years correspond to the initial randomly harvest population (at 0.6 Hr on SSB) the last 20 years correspond to the projections of the managed populations. Lines correspond to the mean values of 250 simulations.

Table 4.1.1 shows the general performance in terms of final SSB and relative changes (trends) for all tested harvest control rules (last ten years of the managed period compared to the last ten years of the unmanaged period): HCR T(2/3) and T(3/5) show a lesser recovery of SSB (by about 20%–40%) compared to the higher increases of the SSB for HCRs T(1/2) and T(1/3) by about 100%. The performances of T(1/2) and T(1/3) are rather similar for the ratios ObsError/IAV between 0,5 and 1, but the ratio of 2, leads to higher increases of biomasses. Regarding the different uncertainty cap levels, for the HCRs T(2/3) and T(3/5) higher SSB recovery rates are obtained for the 50% and 20% UnCap respectively, while for rules T(1/2) and T(1/3) highest SSB recoveries are obtained for 50%–80% UnCap, and the poorest performance is obtained for the 20% UnCap.

Table 4.1.1. Mean Spawning Biomass in the last ten years of the management period and trends of SSB (relative increase or decrease of SSB) relative to the SSB in the last ten years of the unmanaged starting period, according to the ratios of Observation Error over IAV (Columns) and by Harvest Control Rules and Uncertainty Cup levels (Rows), for a harvest rates on the initial (starting) population prior to management of 0.6 (rather highly exploited starting population around but below deterministic F_{MSY}). Uncertainty Cup of 1 means that there is no Uncertainty Cup constraint. MeanStHR means that the Starting mean Harvest Rate is taken a constant F_{proxy} for the future management of the population.

Time Period2	31-40			
Mean Starting HarvestRate	0.6	Mean Starting SSB		
				1,018
Promedio de Mean SSB2	**ObsError/IAV**			
HCR & UnCup	**0.50**	**0.70**	**1.00**	**2.00**
MeanStHR				
0.2	1,043	1,078	984	1,122
0.5	1,166	1,159	1,238	1,184
0.8	1,161	1,184	1,102	1,227
1	962	915	904	680
T(1/2)				
0.2	1,484	1,426	1,444	1,516
0.5	1,827	1,762	1,855	2,038
0.8	1,787	1,909	2,045	2,379
1	1,675	1,635	1,788	2,125
T(1/3)				
0.2	1,449	1,470	1,568	1,631
0.5	1,766	1,896	1,953	2,172
0.8	1,821	1,868	2,021	2,446
1	1,595	1,683	1,845	2,231
T(2/3)				
0.2	1,194	1,201	1,312	1,340
0.5	1,320	1,304	1,400	1,720
0.8	1,298	1,312	1,351	1,611
1	1,032	973	1,042	1,092
T(3/5)				
0.2	1,190	1,205		1,310
0.5	1,135	1,117	1,204	1,357
0.8	969	981	1,125	1,297
1	686	724	682	779

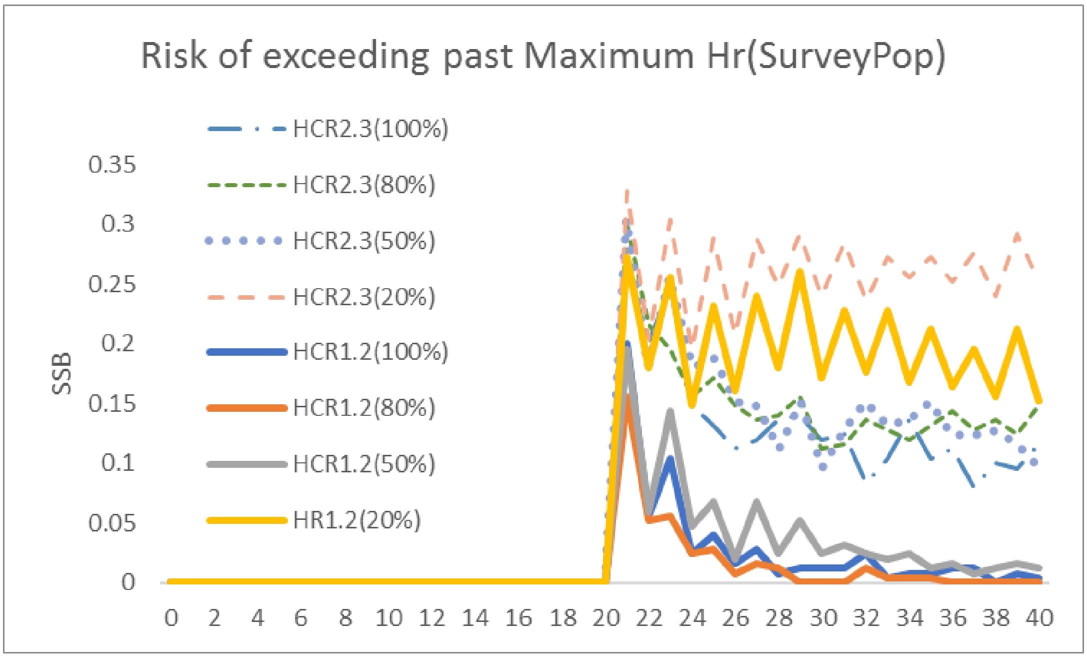
Time Period2	31-40			
Mean Starting HarvestRate	0.6			
Promedio de TrendSSB?2	**ObsError/IAV**			
HCR & UnCup	**0.50**	**0.70**	**1.00**	**2.00**
MeanStHR				
0.2	0	0.15	0.07	0.44
0.5	0.42	0.27	0.25	0.42
0.8	0.21	0.30	0.38	0.45
1	0.01	0.05	-0.01	-0.30
T(1/2)				
0.2	0.60	0.65	0.73	0.74
0.5	1.00	0.91	0.97	1.16
0.8	0.94	1.11	1.19	1.49
1	0.86	0.82	0.94	1.23
T(1/3)				
0.2	0.52	0.74	0.62	0.72
0.5	0.96	1.04	1.11	1.50
0.8	0.95	1.04	1.00	1.62
1	0.70	0.85	1.04	1.37
T(2/3)				
0.2	0.33	0.30	0.40	0.45
0.5	0.40	0.41	0.65	0.98
0.8	0.35	0.34	0.42	0.74
1	0.02	0.00	0.14	0.14
T(3/5)				
0.2	0.27	0.46		0.50
0.5	0.24	0.20	0.30	0.53
0.8	0.07	0.04	0.20	0.39
1	-0.32	-0.27	-0.30	-0.21

The former performance on SSB trends are not always linked to the realized catches produced for each harvest control rule. Table 4.1.2 shows that greater catches are allowed for Rules T(2/3) and T(3/5) for Uncertainty Caps of 50% and 80% and that may explain the poorer increases of Biomasses for those rules compared to the rest. However, T(1/2) with no Uncertainty Cap (1) allows higher catches and higher final SSB increases than rules T(2/3) and T(3/5). This means that it is not only the average of catches what drives final SSB but the strategy of getting them as a function of recent trends as defined by the HCRs. The method 3.3 (corresponding to MeanStHR) allows the highest catches among all the rules but results in modest recoveries compared to rules T(1/2) and T(1/3).

Table 4.1.2. As Table 4.1.1 but containing TAC values over the last ten years of the managed population.

Time Period2	31-40			
Mean Starting HarvestRate	0.6	Mean starting Catch		
				625
Suma de Mean TAC2	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	495	536	485	474
0.5	581	609	618	525
0.8	623	623	561	546
1	558	544	551	496
T(1/2)				
0.2	297	258	240	189
0.5	387	306	252	104
0.8	422	369	272	71
1	520	483	396	189
T(1/3)				
0.2	286	273	273	206
0.5	370	319	269	114
0.8	429	376	308	75
1	478	468	384	152
T(2/3)				
0.2	296	284	303	225
0.5	426	358	355	184
0.8	444	429	377	190
1	488	424	431	323
T(3/5)				
0.2	359	326		266
0.5	361	376	365	253
0.8	344	378	343	254
1	446	352	403	348

Figure 4.1.2 compares for the probabilities during the 20 years managed period of exceeding past harvest rates on the Surveyed populations and the probabilities of falling below minimum past SSB trajectories of the initial unmanaged population (for the anchovy in 9a), subject to in-year advice with HCRules T(2/3) and T(1/2) for the typical 0.25 log observation error of surveys (i.e. at 0.7 times IAV). Regarding the Risks of exceeding past maximum Hr(on Surveyed Population) they diminish with time for rule (T1/2) for uncertainty caps equal or higher than 50% keeping those risks below 5% after the fifth year of application, while risks for rule T(2/3), only diminish to a lesser extent for those uncertainty cap but remaining above 5% risks over the 20 year projections. Concerning the risks of falling below minimum past SSB, the risks diminish sufficiently to levels below 5% for rules T(1/2) for 80% and none Uncertainty Cap (100%) levels, while the other rules either do not diminish or keep the risks above 5%.



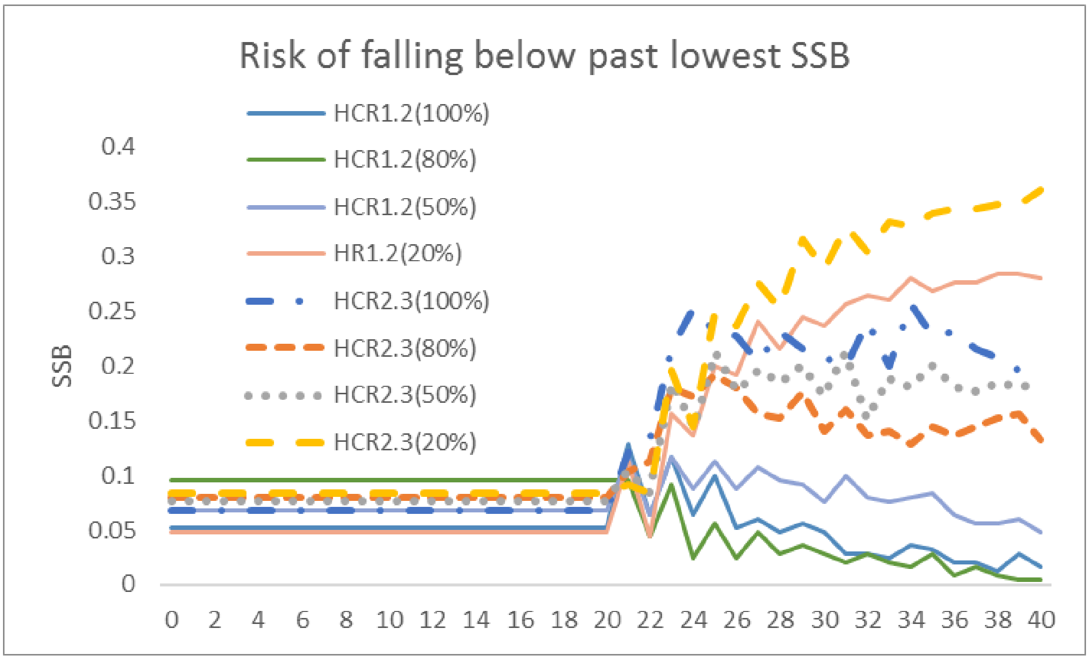


Figure 4.1.2. Trajectories of the Risks of exceeding actual maximum harvest rates on the Surveyed population (during the starting unmanaged period) (Upper graph) and probabilities of falling below minimum SSB of the past unmanaged population (bottom graph) for the managed populations with HCRules T(2/3) and T(1/2) for the typical 0.25 log observation error of surveys (i.e. at 0.7 times IAV) for different Uncertainty Cap levels (in brackets from 20% to 100% -the latter meaning none uncertainty cap applies). The first 20 years correspond to the initial randomly harvest population (at 0.6 Hr on SSB) the last 20 years correspond to the projections of the managed populations. Lines correspond to the mean values of 250 simulations.

Table 4.1.3 shows for all tested HCR the mean harvest rate on SSB over the last ten years of the managed period and the probability of exceeding during that managed period the starting past Harvest rates in the unmanaged period. Concerning the actual harvest rates, most of the results are abnormally huge values as results of occasional collapses of the stock and associated unrealistically high harvest rates demanded by the too high allowed level of catchers in those circumstances. Only Rules T(1/2) and T(1/3) and the MeanStHr result in meaningful harvest rates when applied either without any uncertainty cap (1) or with 80% uncertainty cap, as they avoid mostly those collapses (Table 4.1.4). The likelihood of exceeding maximum past Harvest rates on the Surveyed population during the managed period are very low and keep below 5% for rules T(1/2) and T(1/3) for the method 3.3 (MeanStHR) except for Uncertainty Cap 20%, while for Rules T(2/3) and T(3/5) the likelihood is in all cases above 10%. Certainly, the performance of all HCRs is poorer for the largest ratio ObsError/IAV (of 2).

Table 4.1.3. As Table 4.1.1 but the contents refer to Mean harvest rates on the Surveyed Population for the last ten years of the management population and the Probability of exceeding past Harvest rates on the Surveyed population during the last ten years of the management period compared to the maximum Hr values for the initial 20 years of unmanaged population.

Time Period2	31-40			
Mean Starting HarvestRate	0.6	Mean Starting Hr		
				0.61
Promedio de Hr_SSB2	ObsError/IA			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	633,863	360405.97	310501.68	442448.59
0.5	0.56	9.97	2.69	28524.60
0.8	0.58	0.58	0.57	15.25
1	0.62	0.66	0.74	1.38
T(1/2)				
0.2	372932.80	349590.40	452337.26	272207.93
0.5	0.48	209.27	113.93	594.49
0.8	0.27	0.22	0.16	0.04
1	0.34	0.34	0.26	0.12
T(1/3)				
0.2	828565.96	188414.76	899193.39	145657.89
0.5	2900.70	3.24	558.29	425.15
0.8	0.26	0.24	0.18	8.79
1	0.34	0.33	0.26	0.09
T(2/3)				
0.2	717666.70	457526.33	623488.78	269910.81
0.5	1485.74	1386.81	2063.83	12018.14
0.8	526.73	410.31	161.25	790.68
1	71.79	74.38	102.03	159.07
T(3/5)				
0.2	450917.79	604601.11		330774.45
0.5	90085.61	41681.74	168945.53	99283.93
0.8	17351.02	2853.78	2933.69	5080.30
1	15373.27	665.31	5088.53	1163.02

Time Period2	31-40			
Mean Starting HarvestRate	0.6			
Sumade Prob(AboveMaxHrSPopY)2	ObsErr			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	0	0.18	0.24	0.25
0.5	0.02	0.04	0.06	0.15
0.8	0.00	0.03	0.05	0.10
1	0.01	0.04	0.09	0.20
T(1/2)				
0.2	0.16	0.19	0.19	0.21
0.5	0.00	0.02	0.02	0.05
0.8	0.00	0.00	0.00	0.00
1	0.00	0.01	0.01	0.01
T(1/3)				
0.2	0.17	0.16	0.16	0.14
0.5	0.01	0.01	0.01	0.02
0.8	0.00	0.00	0.00	0.01
1	0.02	0.02	0.02	0.00
T(2/3)				
0.2	0.26	0.26	0.26	0.26
0.5	0.12	0.13	0.12	0.13
0.8	0.10	0.13	0.10	0.11
1	0.13	0.11	0.11	0.09
T(3/5)				
0.2	0.26	0.27		0.27
0.5	0.21	0.23	0.23	0.19
0.8	0.27	0.26	0.24	0.24
1	0.26	0.24	0.24	0.27

Table 4.1.4. Probability of collapse, i.e. of falling below 10% of the unexploited population (according to the Geometric mean Recruitment), for rule T(1/2) for the two cases of harvest rates on the initial (starting) population prior to management: for the healthy starting population (Hr of 0.3) and for the highly exploited starting population (Hr of 0.6) over the 20 or last ten years of the managed period.

		T(1/2)	T(1/2)	T(1/2)	T(1/2)
Init HR	UnCap	**0.2**	**0.5**	**0.8**	**1**
0.3	Prob(Collapse1) (20 Years)	0.027	0.000	0.000	0.000
0.6	Prob(Collapse1) (20 Years)	0.203	0.045	0.0374	0.0374
0.3	Prob(Collapse2) (Last 10 Years	0.040	0.000	0.000	0.000
0.6	Prob(Collapse2) (Last 10 Years	0.2372	0.0216	0.0176	0.012

Discussion

The analysis shows that Rules T(1/2) and T(1/3), applied with no uncertainty cap or with 80% uncertainty cap, outperform other rules in terms of increasing biomasses while still allowing substantial catches (similar or higher to the ones produced with the other HCR). At the same time they tend to avoid exceeding maximum past harvest rates or depressing the population below minimum previous SSB levels (diminishing sharply the risks of collapses). This is shown here for an initially highly exploited population (around deterministic F_{MSY}) and this is also shown for a moderate harvested starting population in the attached WD (Uriarte *et al.*). This confirms the benefits of in-year advice being guided by the most recent information of trend in the populations as shown by HCRs T(1/2) and T(1/3), while other rules T(2/3) and T(3/5) encapsulates longer past trends which are probably not suitable for this fast fluctuating populations. The latter rules show the poorer recovery of the population to higher SSBs and lead to high risks of exceeding maximum past harvest rates (reading huge values in cases of collapses) and high risks (above 5%) of reaching SSB values below lowest SSB values in the unmanaged populations, not improving but worsening with the 20% cap constraint.

Regarding the Uncertainty Cap, 20% uncertainty cap led often to unrealistic mean harvest rates as results of occasional stock collapses even for T(1/2) rule (Table 4.1.4), meaning that such restriction in the year-to-year change of advisable catches can become in risky situations of too high allowable level of catches when drastic biomass reductions occur in these short-lived species. In practice, lowest risks of exceeding maximum past harvest rates and of falling below minimum past SSB (and of collapses) occur for the most flexible HCR (T(1/2) and T(1/3)), for none or for 80% uncertainty cap constrained, which suggest that this is the only way to accommodate the advice to such fluctuating fish resources and of minimizing risky situations.

Globally the higher the ratio of the observation error over the IAV the poorer is the performance of the rules in avoiding too high harvest rates, but this becomes noticeable particularly at a ratio of 2.

Finally, using the Mean past Harvest rate as an F_{proxy} for method 3.3) shows a good consistent result keeping the original harvest rate throughout the whole managed period with acceptable levels of risk of except for the cases of 20% uncertainty cap and/or of very high Observation Error (2), where the performance worsens and leads to some cases of stock collapse too and high risks of exceeding highest past Harvest rates.

During the meeting a similar analysis of the performance of in-year advice for a medium-lived stock like the sardine in the Bay of Biscay (in divisions 8abd, a category 2 stock) was presented as well for comparative purposes with the previous work on short-lived stocks like anchovy. For Sardine in the Bay of Biscay the IAV (without fishery) equals 0.11, while for anchovy the IAV is more than double (0.35). On the other hand, the variability around the stock–recruitment relationship was similar for sardine and anchovy (Sigma around expected log Recruitment), around 0.52 and 0.47 respectively. Results for sardine confirmed globally the better and more conservative performance for in-year advice of rules $T(^{1}/_{2})$ and $T(^{1}/_{3})$ compared to rules $T(^{2}/_{3})$ and $T(^{3}/_{5})$, as the former leads to increasing trends of SSB, for very similar (though slightly lesser) catches than the latter rules, resulting in addition in lower global risks of exceeding past maximum harvest rates or of falling below past minimum observed SSB (particularly evidenced when applied to the management of a highly exploited initial population). It also confirmed the poorer performance of all rules at high levels of ObsError/IAV ratios. However, the results deviated from those of anchovy, in pointing out that optimum Uncertainty Cap was 50% UnCap, as it led to the most precautionary performance in terms of risks for all the rules, and faster increasing rates of the population. Other UnCap could not be discarded (even the 20% at low ObsError/IAV ratios). This contrasting results in terms of Uncertainty Cap between sardine and anchovy is probably related to the far lower IAV of sardine vs. anchovy, and confirms that the election of the best UnCap is to be related to the IAV and the level of ObsError/IAV ratios. However, the analysis of in-year advice for Sardine needed to be finalized, and the results were not included in the Uriarte *et al*. WD attached to this report, although a presentation was laid down in the folder of presentations.

The Working Group considered fruitful and interesting the results obtained so far for the anchovy in 9.a and the preliminary analysis based on the stock of sardine in the Bay of Biscay, but in order to confirm the generalization of these results to other short-lived species, a future workshop was recommended for the first half of 2019 (see Conclusions).

Summary on the Performance of HCRs for In-year advice based on survey trends

Several Conclusions on the selection of In-year advice HCRs for short-lived species based on a Survey index (assessing age 1+ of the managed year) were obtained from the analysis on anchovy-like stock:

- The ratio of Observation Error over the Interannual Variability (IAV) conditions the performance of the tested HCR. The larger it is the harder will be the management.
- Rule ($T(^{1}/_{2})$ and $T(^{1}/_{3})$ informing on the most recent changes in the short-lived populations seems to outperform rules $T(^{2}/_{3})$ and $T(^{3}/_{5})$ for In-year advice (as the latter track longer term changes and allow larger delays between the trends and its application to the management).
- Low Uncertainty Caps worsens the performance of the HCRs for this short-lived species with high IAV. Only uncertainty cap of 80% or No uncertainty cap allows good long-term behaviour of rules $T(^{1}/_{2})$ and $T(^{1}/_{3})$.
- Best candidates for in year advice to short-lived species seems to be $T(^{1}/_{2})$ or $T(^{1}/_{3})$ with no UnCap followed closely with 80% of UnCap.
- Verification of these results for in-year management of other short-lived category 3 stocks and expansion of the analysis to account for some potential modifications of the HCRs is devised for a next coming workshop in the first half of 2019, before final adoption by ICES ACOM (see below).

Other

For short-lived species in category 3 stocks with a survey (or accepted CPUE index) monitoring system, moving from classical DLS methods to In-year advice will be beneficial as it will be using the most of the recent index to manage the resource.

4.2 Inferences from the analysis of management advice based on surplus production models

Overall, the advice rules based on SPiCT show a similar performance for short-lived species as for the longer lived species according to the results of the simulations carried out in the frame of WKLIFE VIII. The relative patterns between the performance of different fractiles of the MSY rules and different P_{PA} levels of the MSY-PA rules are consistent with medium- and long-lived species (see Section 2). The average yield levels are similar across all life-history strategies (cp. Figure 24 to Figure 2.4 and Figure 2.16). However, absolute risk levels are higher for short-lived species reaching up to 20% for two scenarios (Figure 24). The increased risk can be attributed among others to the larger number of non-converged runs (9%), which yields to the re-use of the advice from the previous year - a less precautionary management measure for an overfished stock. The limited suitability of the DLMtool operating model with an annual time-step and of surplus production models in general could contribute to the larger number of non-converged runs and higher risks as well. For future work with respect to short-lived species, see Section 2.5.

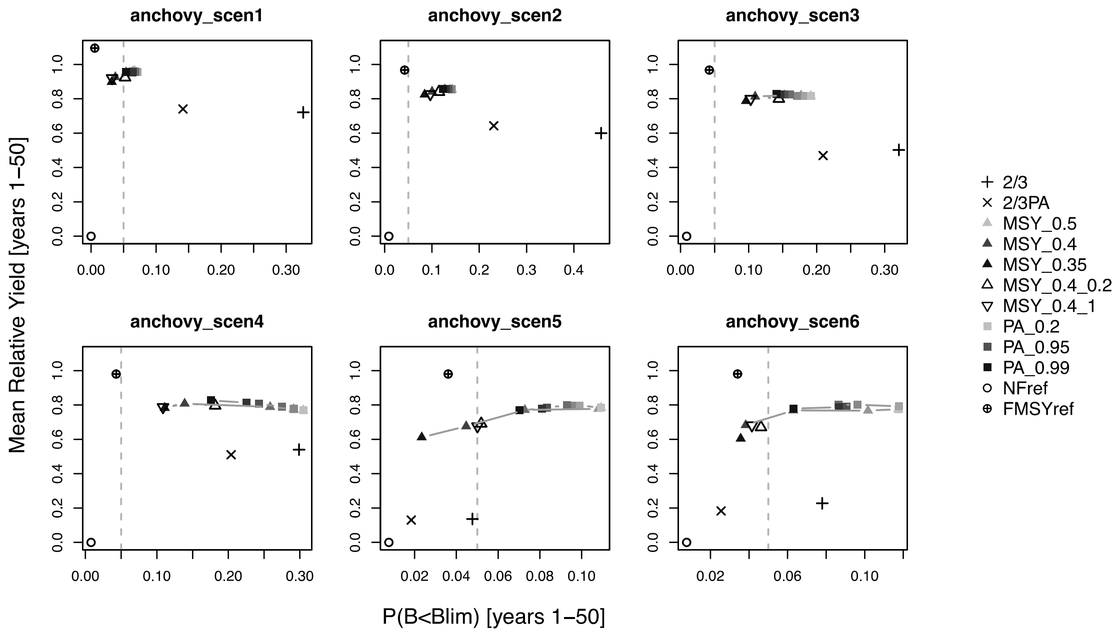


Figure 24. Trade-off graph of mean relative yield and risk 1 for anchovy over all projection years (1–50) and all scenarios with 2/3 and reference rules (NFref & FMSYref). Vertical dashed line represents the reference risk level of 5%. Solid lines between advice rules display the connection of common advice rules which only differ in the fractile or P_{PA}. Intermediate fractile levels not displayed in the legend can be found in Table 2.2.

4.3 MSE testing of catch rules in FLR

A clear conclusion from the simulation testing of WKMSYCat34 catch rules 3.2.1 and 3.2.2 is that these rules are not suitable for stocks with *k*>0.32, which includes short-lived stocks, mainly because of the highly variable nature of these stocks. However, these simulation tests showed that even for the *k*>0.32 stocks, performance of these catch rules improved if time-lags in data provision were reduced and advice was reduced to an annual instead of biennial time-scale (see Figures 3.5 and 3.6 in Section 3). These improvement were not enough to recommend the rules (as presented) for higher *k* stocks, but they indicate the factors that are important to consider when developing appropriate rules for such stocks.

4.4 A new operating model: FLIBM

4.4.1 Description

FLIBM is an individual-based model (IBM) the simulation of fish or invertebrate populations, which may provide a flexible operating model framework for future WKLIFE explorations. The IBM is parameterized with functions describing life-history processes in terms of length (e.g. growth, mortality, maturity). This facilitates the generation of length–frequency data, which is used in some data-limited indicators and assessment approaches. Nevertheless, individuals' age is also followed in order provide both length- and age-based summary statistics in the form of `FLStock` objects (see FLR project: http://www.flr-project.org/). Following the FLR framework allows for integration in other FLR-related resources.

The main sequence of processes in the IBM operating model are as follows:

1) ***update*** - Updates the states of individuals at the beginning of a time-step (e.g. mortality rates, maturity).
2) ***reproduce*** - Creates new individuals based on spawning schedule and stock–recruitment relationship.
3) ***die*** - Determines individuals that die, either naturally or from fishing.
4) ***record*** - Records the state of the population in FLStock objects (e.g. numbers, mean weight by age and length, mortality rates, etc.).
5) ***remove*** - Removes dead individuals.
6) ***grow*** - Controls the growth of surviving individuals through the time-step.

Generally, the model should be run at a sufficiently large number of interannual time-steps (default = 12, i.e. monthly) to produce realistic behaviour and summary indices.

The main source of variability at the individual level is in terms of growth and maturity; *e.g.* von Bertalanffy growth function (VBGF) parameters (K, L_{inf}) and length-at-maturity (L_{mat}) are drawn for each individual at their birth.

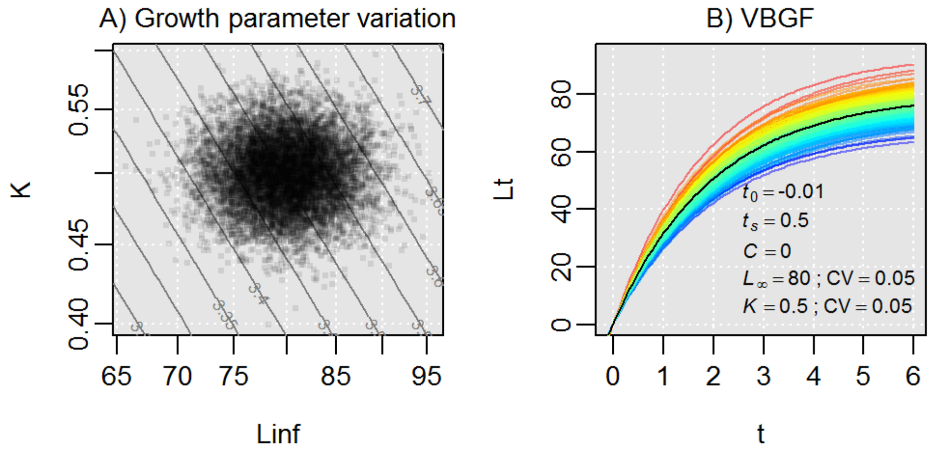


Figure 1. Variation in individual growth.

4.4.2 Example simulation

The following example demonstrates the setup and running of FLIBM. An initial object can be created with the `create.FLIBM` function, which contains the basic structure of the class along with the default functions for controlling population dynamics. These controlling functions, as well as their parameters, can be set by the user to the specifications of the stock. The general dimensions of the FLStock objects are also provided by the user, and are used to record summary statistics of the IBM through the simulation time:

1) ***age*** and ***length*** - Classes of age or length. The largest values are considered as the "plus group";
2) ***year*** - Calendar year;
3) ***unit*** - Division of the population (e.g. by sex);
4) ***season*** - Temporal strata shorter than year;
5) ***area*** - Spatial stratification;
6) ***iter*** - Replicates.

In addition, the user provides the units that will be used for numbers (`n.units`) and weights (`wt.units`).

```
stk <-create.FLIBM(
length =0:85, age =0:6,
year =ac(2000:2009), unit ="all",
season =ac(1:12), area ="all", iter ="all",
n.units ="1e3", wt.units ="kg"
)
summary(stk)

##            Length Class   Mode
## growth         2  -none-  list
## rec            3  -none-  list
## m              1  -none-  list
## harvest        2  -none-  list
## n.units        1  -none-  character
## wt.units       1  -none-  character
```

```
## inds          1  -none-  list
## stock.l       1  FLStock S4
## stock.a       1  FLStock S4
## length.a    840  FLQuant numeric
## age.l     10320  FLQuant numeric
```

The slots `growth`, `rec`, `m`, and `harvest` are lists containing controlling functions, their associated parameters, and (in some cases) covariates. These can be adapted to the specifications of the stock.

```
# adjust natural mortality function
stk$m$model <-function(length){(1-0.7)*exp(-length*0.02)+0.7}

# adjust recruitment function parameters
stk$rec$params['rmax'] <-1e4

# adjust Fbar in FLStock
range(stk$stock.a)[c("minfbar", "maxfbar")] <-c(1,4)

# pulsed recruitment with yearly variability
stk$rec$params$season_wt[] <-0
stk$rec$params$season_wt[3:5] <-c(0.25, 1, 0.25)
stk$rec$covar[] <-rlnorm(n =dim(stk$rec$covar)[2],
meanlog =0, sdlog =0.5)

# seasonal growth oscillation
stk$growth$params['C'] <-0.75

# fishing mortality
stk$harvest$params['FM'] <-0.7
```

Finally, the stock is advanced through time using the `adv.FLIBM` function, where the span of the advancement is specified. In the following example, a period of spinup precedes the advancement. The resulting numbers by age class are shown in Figure 2.

```
# spinup and advance
stk <-spinup.FLIBM(obj = stk, monitor =FALSE)
stk <-adv.FLIBM(obj = stk, year =ac(2000:2009), monitor =FALSE
)
```

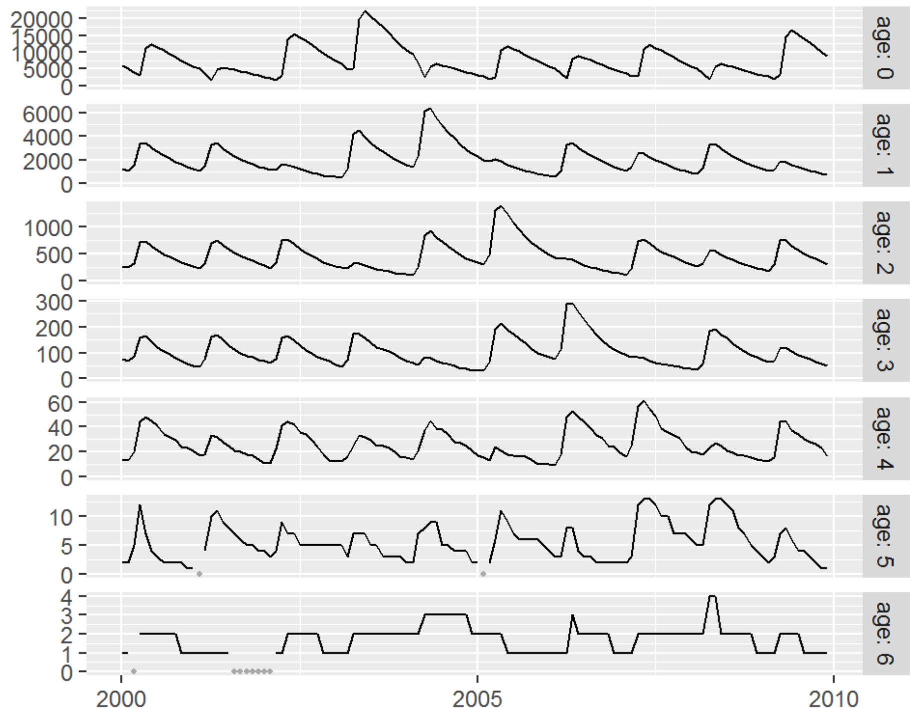


Figure 2. FLIBM stock numbers.

Summaries of stock numbers and catches are also provided by length (Figure 3), allowing for the calculation of length-based indicators and integration with length-based assessment methods.

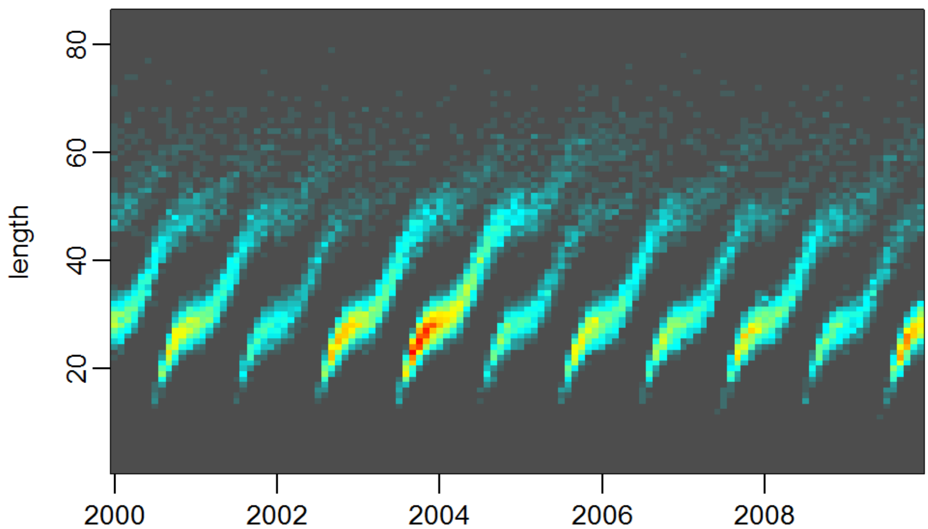


Figure 3. FLIBM length–frequency data output.

4.4.3 Outlook for use in WKLIFE

FLIBM was presented to WKLIFE VIII as a possible operational model for the testing of length-based indicators and assessment methods. The FLIBM approach will generally require more computational time than the other methods used by the group, which may be a limiting factor in scenarios requiring many iterations. Nevertheless, the flexible framework allows for explorations of special cases where more detailed output is desired.

The group commented that the model may be of particularly useful in the simulation of short-lived species for which finer temporal resolution is required. Another area of interest was to use the model to address observation error within a Management Scenario Evaluation (MSE) context.

Future plans include the expansion of the framework to allow for MSEs, which will be used within the EU-funded tender project, PROBYFISH (*Protecting bycaught species in mixed fisheries*). The work will address the accuracy and bias of length-based indicators and assessment methods for use in describing the condition of data-limited bycatch species. It is planned that the initial results of this work will be presented at next year's WKLIFE meeting.

4.5 Performance of HCRs for in-year advice based on survey trends

Several Conclusions on the selection of in-year advice HCRs for short-lived species based on a Survey index (assessing age 1+ of the managed year) were obtained from the analysis on anchovy-like stock:

- The ratio of Observation Error over the Interannual Variability (IAV) conditions the performance of the tested HCR. The larger it is the harder will be the management.
- Rule ($T(^1/_2)$ and $T(^1/_3)$ informing on the most recent changes in the short-lived populations seems to outperform rules $T(^2/_3)$ and $T(^3/_5)$ for In-Year advice (as the latter track longer term changes and allow larger delays between the trends and its application to the management).
- Low Uncertainty Caps worsens the performance of the HCRs for this short-lived species with high IAV. Only uncertainty cap of 80% or No uncertainty cap allows good long-term behaviour of rules $T(^1/_2)$ and $T(^1/_3)$.
- Best candidates for in year advice to short-lived species seems to be $T(^1/_2)$ or $T(^1/_3)$ with no UnCap followed closely with 80% of UnCap.
- Verification of these results for in-year management of other short-lived category 3 stocks and expansion of the analysis to account for some potential modifications of the HCRs is devised for a next coming workshop in the first half of 2019, before final adoption by ICES ACOM (see below).

Other

- For short-lived species in category 3 stocks with a survey (or accepted CPUE index) monitoring system, moving from classical DLS methods to In-Year advice will be beneficial, as it will be using the most of the recent index to manage the resource.

4.6 Future directions

Several suggestions for better definition of In-Year advice best HCR were put forward such as:

- Better definition of Sustainable harvest rates (F_{proxy}) for these short-lived category 3 stocks.
- Further exploration of the need of any uncertainty cap.
- Assessing the influence of the starting catch and proposing ways to select or estimate an appropriate one.
- Assessing the benefits of including another factor in the in-year advice HCRs to account for the current status relative to an Index threshold value as a trigger to amplify the downward correction trends in case the last index falls below the Index threshold. (Aligned with factor b of equation 3.2.1.1 in ICES, WKMSYCAT34 report (ICES CM 2017/ ACOM:47). The particular case of triggering a closure of the fishery can be included within this framework.
- Assessing the potential for maximum or minimum TAC values.
- Assessing the potential benefits for the In-Year advice HCR of having asymmetrical allowance of catch changes for upwards vs. downwards trends.
- Assessing if the value of the information content of the Index (in terms of age structure relative to the managed population) affects the selection of the HCR to be applied in these species for in year advice (between the competing rules T($^1/_2$), T($^1/_3$)…).

4.7 Conclusions

During WKLIFE VII and WKLIFE VIII, a number of promising approaches for short-lived species have been presented and discussed; however, the results were still preliminary and the models still need improvement.

These considerations lead to the conclusion that a workshop on assessment, harvest control rules and MSE for data-limited short-lived species is most needed: despite the fact that the species currently in the ICES list are just a handful, the discussions and outcomes will be relevant to a wider range of situations. The workshop should be held in the first half of 2019.

<u>Recommendation</u>: Early in 2019, convene an ICES Workshop on DLS short-lived species that addresses both assessment methods; e.g. seasonal SPiCT, and long-term management strategy evaluations; building on the work of WKLIFE VII and WKLIFE VIII. Two co-chairs are recommended (Andrés Uriarte, Spain and Piera Carpi, UK). It is suggested that the workshop focus on all the short-lived stocks in Categories 3 and 4 that ICES is required to provide advice for. Stocks to be considered include:

- Anchovy (*Engraulis encrasicolus*) in Division 9.a (Atlantic Iberian waters);
- Sprat (*Sprattus sprattus*) in Division 3.a (Skagerrak and Kattegat);
- Sprat (*Sprattus sprattus*) in divisions 7.d and 7.e (English Channel);
- Striped red mullet (*Mullus surmuletus*) in Subarea 4 and divisions 7.d and 3.a (North Sea, eastern English Channel, Skagerrak and Kattegat);
- Herring (*Clupea harengus*) in Subdivision 31 (Bothnian Bay).

5 MSE testing of catch rules for elasmobranchs

5.1 Introduction

Elasmobranchs are cartilaginous fish, most of which are k-selected species with relatively slow growth, late maturity, large adult size, and few developed juveniles. The elasmobranch species most vulnerable to overexploitation tend to be larger sized, slow growing, late maturing and long-lived (Smith *et al.*, 1998; Dulvy *et al.*, 2000). Extinction risk was found to be associated with habitat (deep-sea species higher risk) and reproductive strategy (viviparous higher risk than oviparous) (García *et al.*, 2008). In particular, stocks with maturation occurring at relatively large size and slow growth, are vulnerable to recruitment failure as the size range of mature individuals become truncated and decimated size classes are slowly replenished due to long generation time. In contrast, small-bodied species tend to be more productive with a higher rebound potential (Stevens *et al.*, 2000).

Elasmobranch recruitment is closely linked to the number of mature females, which leads to a fast reduction in recruitment with decreasing number of mature females in the populations, and limits the recovery from overfishing when SSB is low and the potential of replenishment by large incoming cohorts is small (Cailliet *et al.*, 2005). Instead of maximizing yield, the focus of management for elasmobranch stocks should therefore be on the protection of the reproductive potential.

A number of length-based indicators are available and some have been identified as potential suitable to summarize catch length distributions with regard to exploitation of juveniles, large adults and optimal yield (ICES, 2015; Miethe and Dobby, 2015; Miethe *et al.*, 2016; ICES, 2018b). The mean length in the catch with a reference point based on F=M proxy for MSY has been suggested (Jardim *et al.*, 2015). The reference point is derived accounting for L_c and M/k. However, it was found that $\bar{L}$ and its respective reference point $L_{F=M}$ perform well only if the length at first capture L_c>L_{mat}(Jardim *et al.*, 2015; Miethe and Dobby, 2016). For many elasmobranch stocks, L_c is typically lower than L_{mat} (ICES, 2018c).

Cuckoo ray, *Leucoraja naevus*, with demersal habitat in the Northeast Atlantic. Spawning can occur throughout the year, but was observed to be typically highest at the beginning of the year (Maia *et al.*, 2012). Rays are often caught as bycatch in mixed demersal fishery for roundfish and flatfish (ICES, 2017). Estimates of natural mortality for this stock are typically scarce. Values of 0.3 for females and 0.4 for males have been suggested (Pauly, 1980; Gallagher *et al.*, 2005; Then *et al.*, 2015).

Reference points for length-based indicators are sensitive to the value of M/k, the ratio of natural mortality M and the von Bertalanffy growth constant k, which determines the shape of the equilibrium length distribution of an unfished population (Hordyk *et al.*, 2015; Jardim *et al.*, 2015; ICES, 2016). Rays, Rajidae, exhibit ratios of M/k similar to bony fish (Frisk *et al.*, 2001). Life-history parameters for Cuckoo ray in the Irish Sea are listed in Annex 1 (Table A1). A relatively high M/k ratio is observed of 1.4 and 1.5 for males and females, respectively. These relatively high values of M/K (>1) do not limit the application of the length-based indicators (ICES, 2018a). A change in exploitation level and stock status is expected to cause a sufficient change in the catch length distributions and in the length-based indicators.

With the help of length-based population models and management strategy evaluation (MSE), we test the use of length-based indicator $\bar{L}$ together with respective reference points in harvest control rules (HCRs) to recover an overexploited stock of Cuckoo ray.

We investigate different values of L_c and misspecification of M (i.e. M/k). We test different levels of sampling intensity, and uncertainty in CPUE index. The model and assumptions are described in detail in Annex 1.

5.2 Results

5.2.1 HCR with LBI ratio $\bar{L}/L_{F=M}$ only

We simulate an overexploited stock, which has been harvested at constant yield with an $L_c<L_{mat}$. In this baseline scenario, the stocks collapse in all simulation runs (Annex 1, Figure A5). A harvest control rule based only on the ratio of $\bar{L}$ and the reference point $L_{F=M}$ alone may recover an overexploited stock when L_c is below L_{mat} (Figure 25, Table 3). The risk to fall below $25\%SSB_0$ in the last 10 years of the simulation period is 85%.

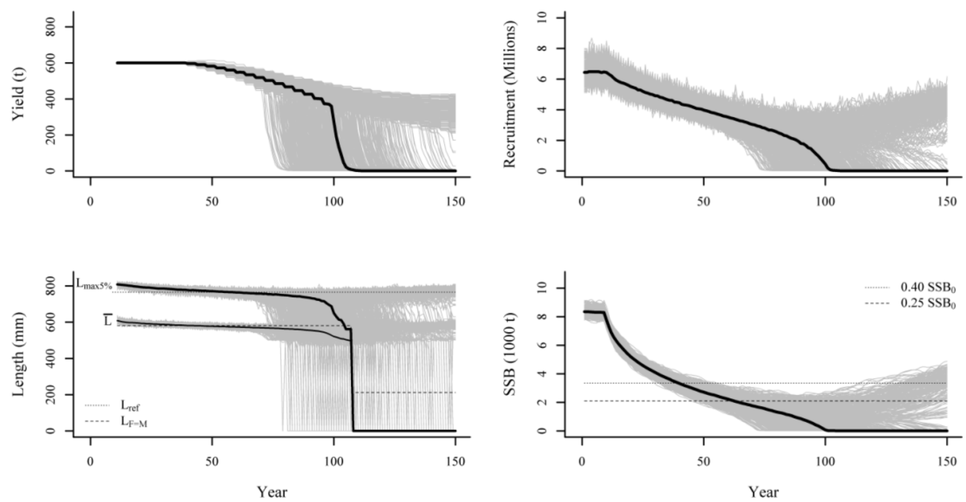


Figure 25. HCR $\bar{L}/L_{F=M}$, $L_{50\%}$=450, initial TAC of 600t, 1000 simulations.

In contrast, fishing mortality only on mature individuals ($L_c>L_{mat}$) facilitates stock recovery using a simple HCR based on mean length. For $L_{50\%}$=600 of the selectivity ogive, a proportion of mature individuals are not subject to fishing mortality. At constant yield of 725t leads to a decrease of SSB to very low levels, but some low level recruitment can occur (Annex 1, Figure A6). In this case, the HCR $\frac{\bar{L}}{L_{F=M}}$ can lead to recovery of overexploited stocks (Figure 26, Table 3). The risk of falling below biomass thresholds decreases in scenarios with even higher values of L_c, but leads to a trade-off in potential yield even in simulated recovered stocks.

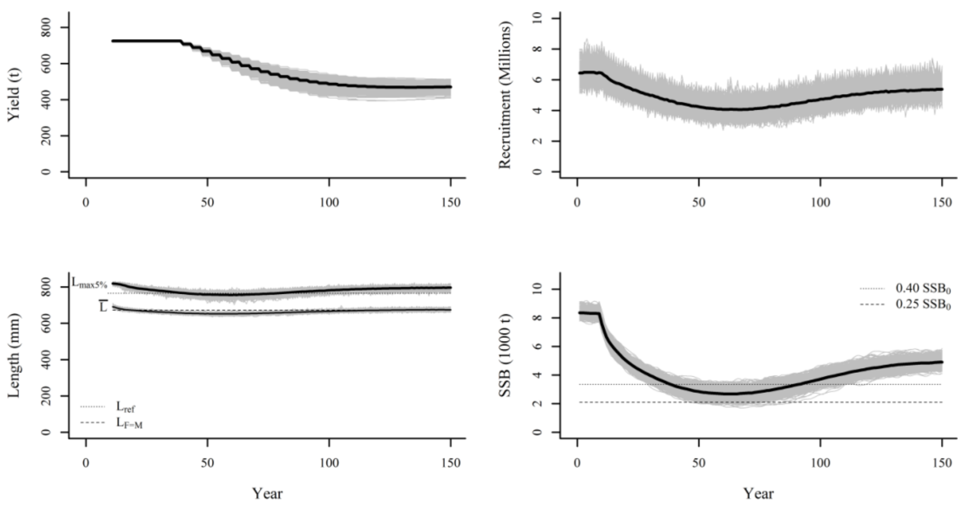


Figure 26. HCR $\bar{L}/L_{F=M}$, $L_{50\%}$=600, initial TAC of 725t, 1000 simulations.

Table 3. Risks to fall below SSB thresholds using the simple HCR $\bar{L}/L_{F=M}$ for different selectivity, $L_{50\%}$, in 1000 simulations.

Years	111-120	121-130	131-140	141-150	HCR	$L_{50\%}$
0.25 SSB	100	100	100	100	Constant yield	450
0.40 SSB	100	100	100	100		
0.25 SSB	94.1	91.7	87.5	85	$\bar{L}/L_{F=M}$	450
0.40 SSB	100	99.6	98.7	93.5		
0.25 SSB	100	100	100	100	Constant yield	600
0.40 SSB	100	100	100	100		
0.25 SSB	0	0	0	0	$\bar{L}/L_{F=M}$	600
0.40 SSB	0.1	0	0	0		

The assumption of F=M for the mean length reference point leads to differential exploitation level with varying number of fished size classes. At asymptotic selectivity and $L_c<L_{mat}$ more individuals are subject to fishing at F, increasing the overall exploitation level compared with $L_c>L_{mat}$. In Figure 27, we compare the theoretical mean length in the catch at SPR of 40% under equilibrium conditions to $L_{F=M}$ for a range of L_c values. For $L_c<L_{mat}$, the figure shows that the reference point $L_{F=M}$ would result in a SPR lower than 40%. For $L_c \geq L_{mat}$, the reference point is appropriate and coincides with an SPR of at least 40% (Figure 27). For comparison, the actual simulated mean lengths at SPR 40% are plotted (black dots). It can be noted when L_c is low ($<L_{mat}$) the mean length of a simulated overexploited stock, characterized by non-equilibrium dynamics with decreasing SSB and recruitment, are higher than their theoretical values. Under non-equilibrium conditions, the slightly higher mean length simulated is caused by the presence of paste more abundant cohorts (older, larger size) as well as the reduction in recruitment with overexploitation (less abundant incoming cohorts) in the catch length distribution. Temporarily, this leads to a relatively smaller number of small individuals in the catch and larger mean length than expected under equilibrium conditions. The reference point underestimates the mean length a decreasing stock, which increases the risk to fall below biomass thresholds when used in a HCR.

If possible, at asymptotic selectivity the L_c should be above L_{mat} to facilitate management with a HCR using the reference point $L_{F=M}$.

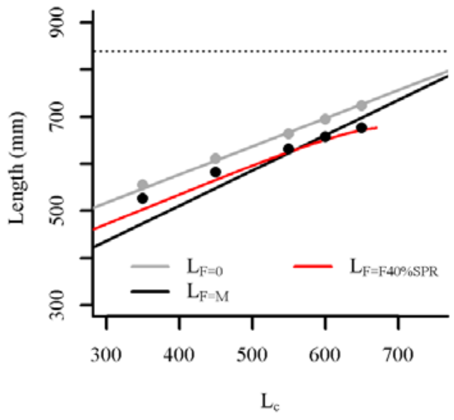


Figure 27. Reference points $L_{F=M}$ for different values of L_c. Simulated values of overexploited stock at SPR=40% (black dots). Unexploited stock at equilibrium in grey. Theoretical mean length at SPR=40% in red.

5.2.2 Testing a different spawning stock–recruitment relationship

The performance of HCRs depends on the assumption of the spawning stock–recruitment relationship. The calculation of the reference point $L_{F=M}$ depends on the assumption of constant recruitment. If recruitment decreases strongly with SSB, the number of smaller individuals in the catch decreases accordingly, potentially affecting the value of mean length in the catch. An alternative recruitment relationship was tested using a survival function as detailed in the Annex 1, Figure A4 (Taylor *et al.*, 2013).

Using this function the unexploited equilibrium in the simulated population depends on the parameter choice. A population can go extinct, explode, equilibrate or oscillate in limit cycles. Therefore equilibrium dynamics should be investigated before implementation in a MSE. It should be noted that a Beverton–Holt relationship is easier to parameterize (only two parameters, no oscillations). Parameters for the Taylor relationship are selected to guarantee an unexploited equilibrium. We find that, in comparison, the selected Beverton–Holt relationship shows a stronger reduction in recruitment with decreasing stock size as expected for elasmobranch life histories (Figure 28). If the recruitment is relatively constant or decreases little with decreasing SSB, the HCRs will perform better (Figure 29). This can be explained by the larger number of small individuals in the catch with decreasing SSB, which lead lower mean length values for the same level of SSB and stronger downward adjustment of TAC by the HCR. The stocks recover more quickly reducing the risk of collapse. In the following scenarios, we continue to use the Beverton–Holt relationship relating number of mature females to recruits.

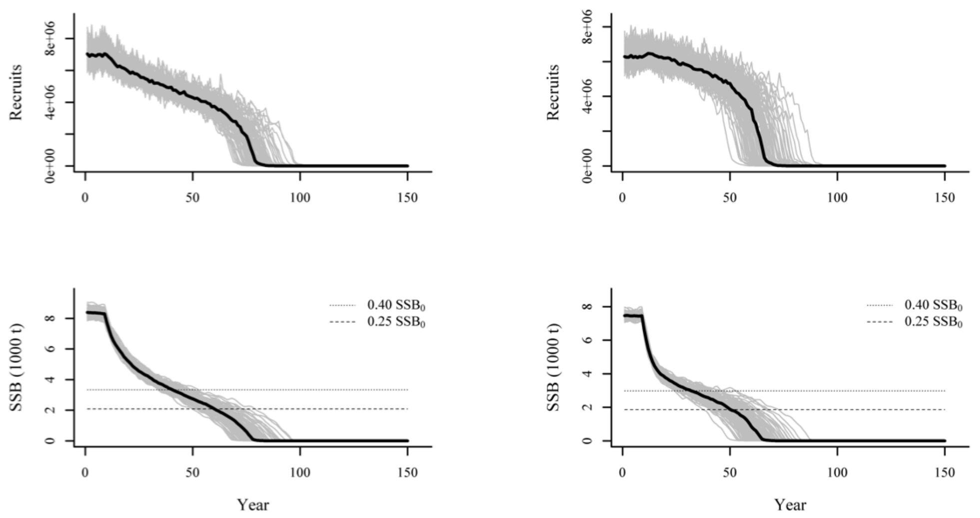


Figure 28. Constant yield baseline scenario, $L_{50\%}$=450, 100 simulations. Left panels Beverton–Holt, right panels Taylor *et al.* (2013).

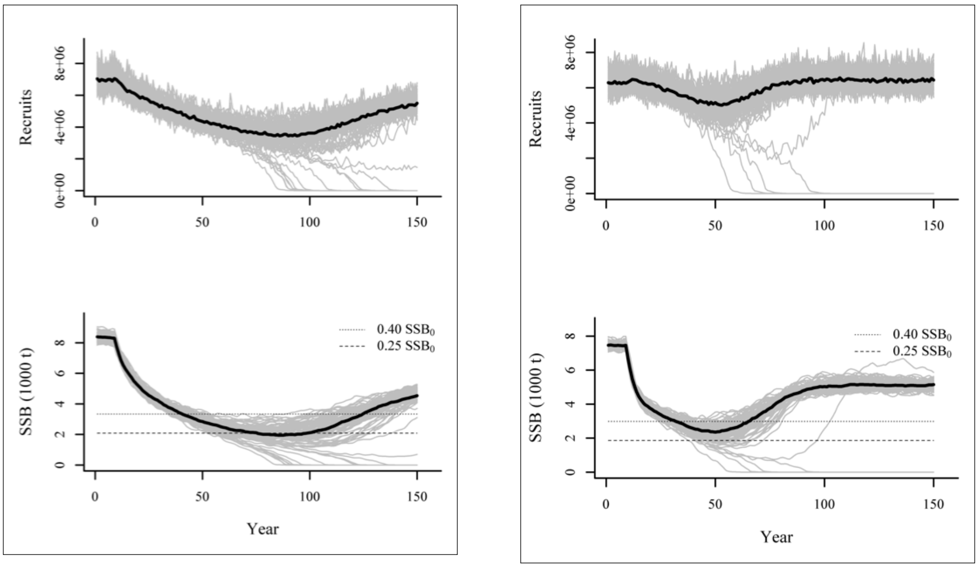


Figure 29. HCR $\bar{L}/L_{F=M}$, $L_{50\%}$=450, 100 simulations. Left panels Beverton–Holt, right panels Taylor *et al.* (2013).

5.2.3 Combined HCR with $\bar{L}/L_{F=M}$ and CPUE 2-over-3 rule

We have seen that at L_c<L_{mat}, HCRs based on mean length only may not be sufficient to recover stock. Instead HCRs combining mean length ratios with a stock index (CPUE) and allowing a stronger reduction in TAC (constraint -25%, 15%) can improve the performance. At decreasing abundance, as indicated by CPUE, the TAC is adjusted downward more rapidly using a combined HCR with indicator ratio and stock index (CPUE, 2-over-3 rule) and succeeds in recovering an overexploited stock (Figure 30).

The risk of falling below 25%SSB_0 threshold at the end of the simulation period is zero (Table 4). A stronger asymmetric constraint (-25%, 5%) leads to very similar results, with the median being slightly lower, closer to the threshold of 40%SPR (therefore slightly higher risk to be below).

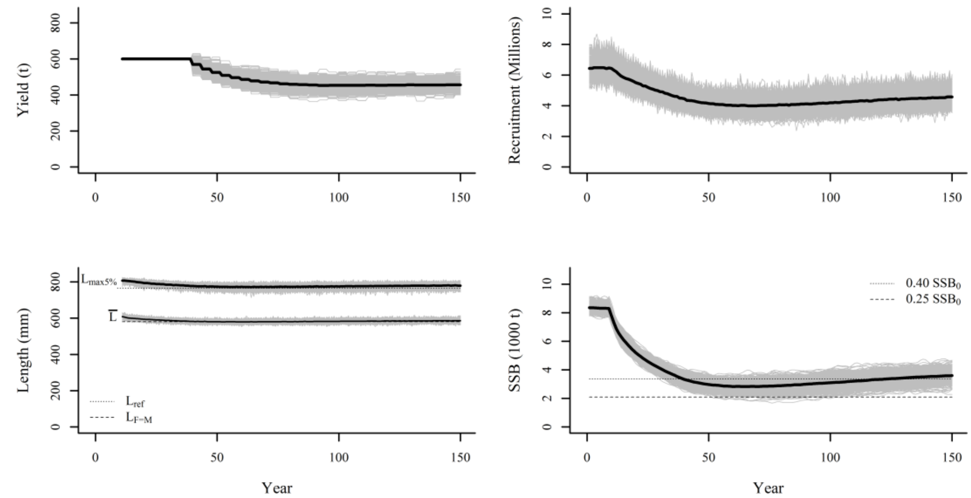


Figure 30. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, initial TAC of 600t, 1000 simulations.

Table 4. Risks to fall below SSB thresholds using the HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, in 1000 simulations.

Years	111-120	121-130	131-140	141-150	HCR
0.25 SSB	100	100	100	100	Constant yield
0.40 SSB	100	100	100	100	
0.25 SSB	0	0	0	0	Combined (-25%, 15%)
0.40 SSB	62.5	51	37.8	27.9	
0.25 SSB	0.1	0	0	0	Combined (-25%, 5%)
0.40 SSB	65.9	57	43.3	34.6	

5.2.4 Parameter misspecification of natural mortality

A misspecification of natural mortality M to calculate the reference point $L_{F=M}$, can lead to inappropriate HCR. If M is significantly underestimated, we assume higher survival and more extended equilibrium size distributions of unexploited stocks than with correct M. Therefore, the respective value of $L_{F=M}$ will be higher due to the lower mortality. With higher reference points the HCRs lead to a lower risk to fall below biomass thresholds, as a reduction in TAC is triggered at higher indicator values (Table 5). In contrast, if M is overestimated, reference points are lower leading to higher level of fishing mortality and higher risk of stocks falling below biomass thresholds (Figure 31, left panels). The effect of misspecification of M on risk is rather small when L_c is larger than L_{mat}, because the HCR is precautionary enough in recovering an overexploited stock (Annex 1, Figure A7). Similarly, misspecification of other life-history parameters leading to lower reference points can increase the risk of stocks falling below biomass thresholds. With uncertainty in life-history parameters and exploitation of immatures more precautionary HCRs are therefore recommended. The combined HCR using mean length and CPUE index performs well also with misspecification in M (Table 6, Figure 31right panels).

Table 5 Risks to fall below SSB thresholds, in 1000 simulations with 10% error in M, using the simple HCR $\bar{L}/L_{F=M}$, $L_{50\%}$=450, in 1000 simulations.

YEAR	111-120	121-130	131-140	141-150	HCR
0.25 SSB	6.3	4	3	2.9	$\bar{L}/L_{F=M}$ -10% error M
0.40 SSB	43.2	12	4.4	2.9	
0.25 SSB	94.1	91.7	87.5	85	$\bar{L}/L_{F=M}$ no error
0.40 SSB	100	99.6	98.7	93.5	
0.25 SSB	100	100	100	100	$\bar{L}/L_{F=M}$ +10% error M
0.40 SSB	100	100	100	100	

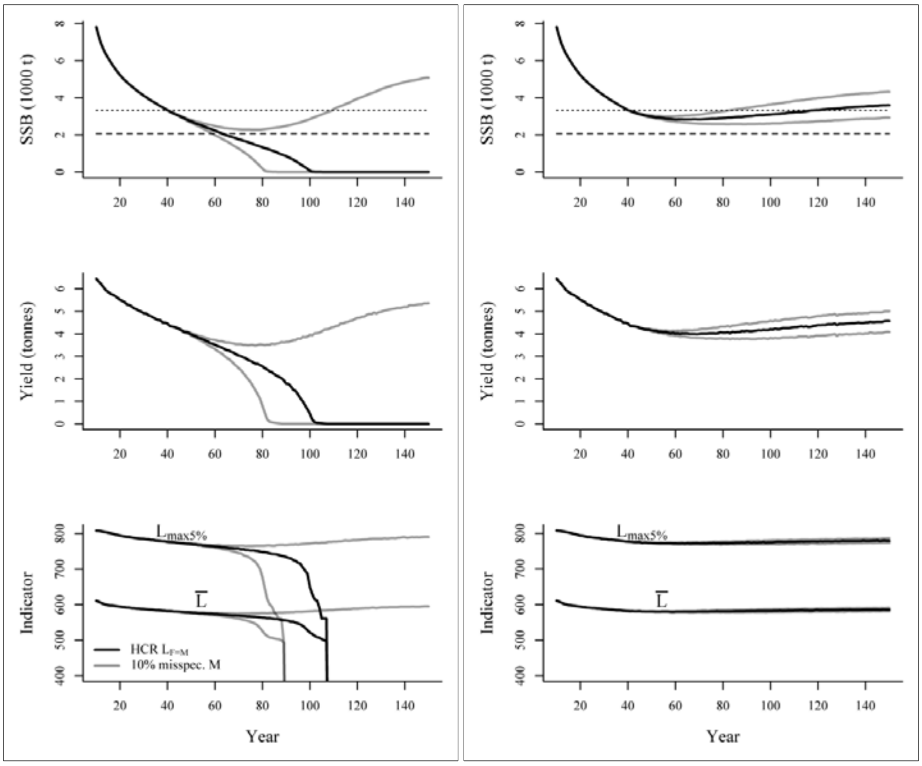


Figure 31. Misspecification of M (±10%, in grey), with $L_{50\%}$=450. Median values of 1000 simulations for Left panels HCR $\bar{L}/L_{F=M}$ and Right panels HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%).

Table 6. Risks to fall below SSB thresholds, in 1000 simulations with 10% error in M, using HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%) with $L_{50\%}$=450, in 1000 simulations.

Year	111-120	121-130	131-140	141-150	HCR
0.25 SSB	0	0	0	0	combined -10% error M
0.40 SSB	6.5	2.6	1	0.4	
0.25 SSB	0	0	0	0	combined no error
0.40 SSB	62.5	51	37.8	27.9	
0.25 SSB	5	3.8	2.5	1.6	combined +10% error M
0.40 SSB	97.3	95	93.3	91.8	

Testing different resampling rates to derive length-based indicators

So far, it is assumed that 1% of catches are subsampled to derive mean length indicator (Annex 1, Figure A8). As the percentage of subsampled catches decreases the indicators can become more variable. The effect of interannual variability of the indicator is reduced because the HCR uses the average indicator ratio of the most recent four years. However, for the simple HCR $L_{F=M}$, very low sample size can lead to higher risk of collapse if the variability of the indicator becomes very large (Annex 1, Figure A11). To keep the mean length indicator relatively stable, we find an unbiased sampling of the catch size distribution with at least 100 individuals in the most abundant catch size class is sufficient. Since the combined HCR is driven mainly by the CPUE index, HCRs perform well also for low sample sizes (Figure 32–Figure 35). It should be ensured the sampling occurs unbiased and is representative of the fishery on the respective stock.

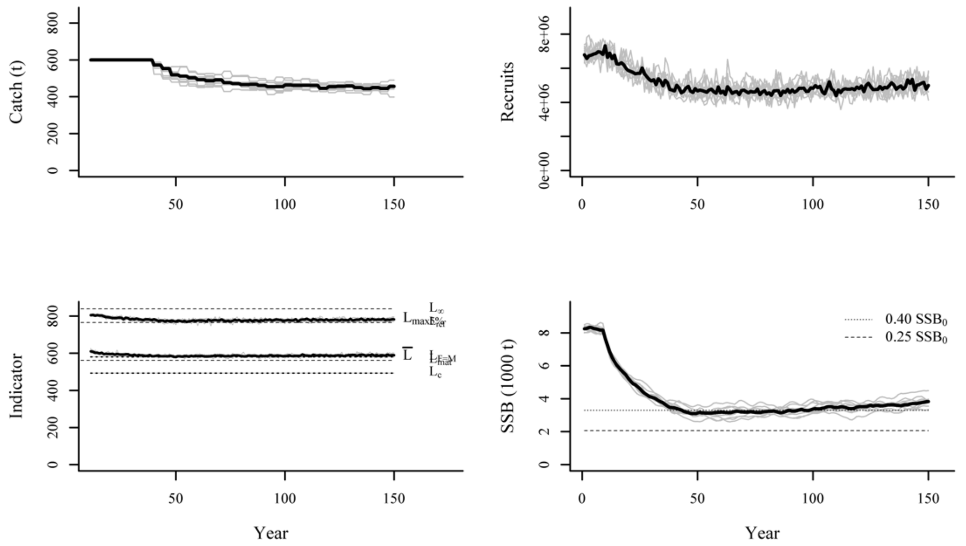


Figure 32. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, sampling distribution at 0.2% unbiased subsampling.

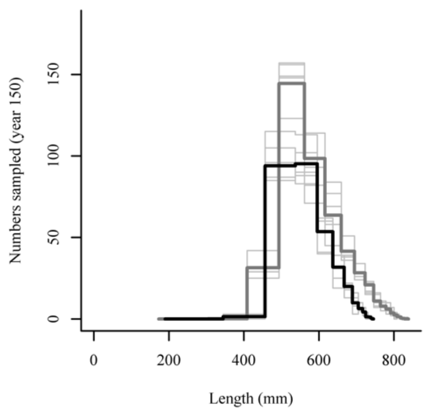


Figure 33. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, sampling distribution at 0.2% unbiased subsampling, ten simulations.

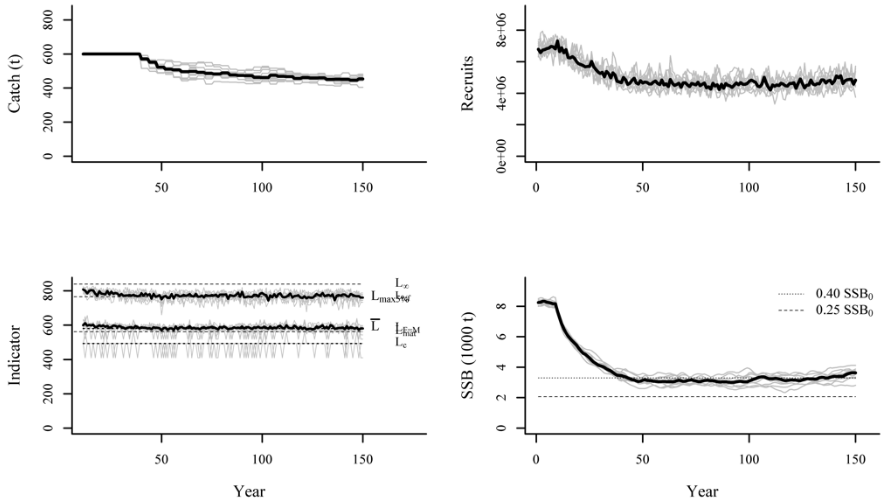


Figure 34. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, results at 0.04% subsampling, ten simulations.

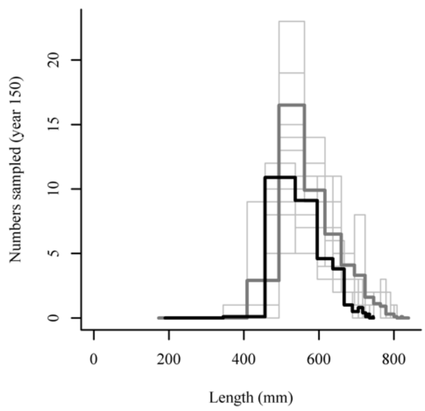


Figure 35 HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, sampling distribution at 0.04% subsampling.

5.2.5 Alternative L_c

The reference point $L_{F=M}$ is calculated with the assumption of knife-edge selectivity. For indicator calculation L_c is often defined as the length at 50% of the mode of the size distribution approximating the inflexion point of the selectivity ogive (Jennings *et al.*, 2001; ICES, WKLIFE 2012). Alternatively, L_c can be calculated as the mode of the size distribution representing the maximum selectivity of the ogive and full selectivity (ICES, 2018c; ICES, 2018b). Calculating L_c by using the mode of the distribution, assumes there is no exploitation on individuals smaller than L_c. Overestimating L_c should lead to higher reference points thereby reducing the risk to fall below biomass thresholds.

In the simulation model, the difference in performance of the combined HCR with either methods to approximate L_c are relatively small (Figure 36). The median SSB in the last five years of 100 simulation were 39.8 (L_c length at 50% of mode) and 40.5 (L_c mode). In this length-based model, length classes at small size are few but relatively large and the selectivity ogive is relatively steep such that estimated L_c is similar to both methods. As in reality length classes at small size may have smaller bin width, it is recommended to calculate L_c as the mode of the distribution as suggested by ICES (2018c).

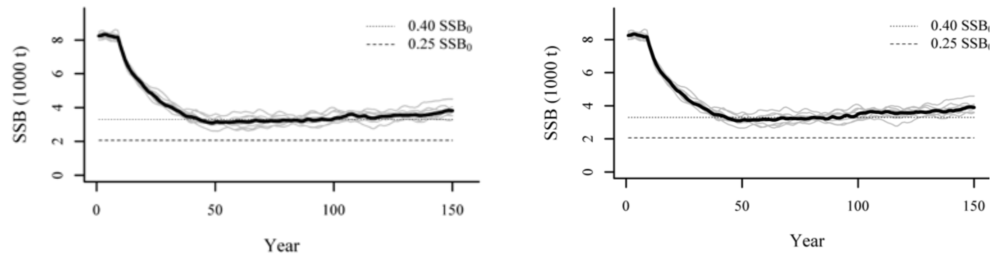


Figure 36. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, 100 simulations. Left L_c is calculated as length at 50% of the mode of the sample size distribution, right L_c is calculated the mode of the sample size distribution.

5.2.6 Frequency of assessment

To further improve the performance of the quadrennial HCRs, a more frequent assessment and adjustment of the TAC can be recommended. For example, a biennial assessment would allow for a fast reduction in TAC when a stock becomes overexploited, reducing the risk to fall below biomass thresholds. This allows for recovery of an overexploited stock using the simple HCR $L_{F=M}$ (Annex 1, Figure A17). We find that the combined HCR, with mean length and CPUE index, performs slightly better in a biennial assessment, with lower variability of the SSB results than in a quadrennial assessment (Figure 37).

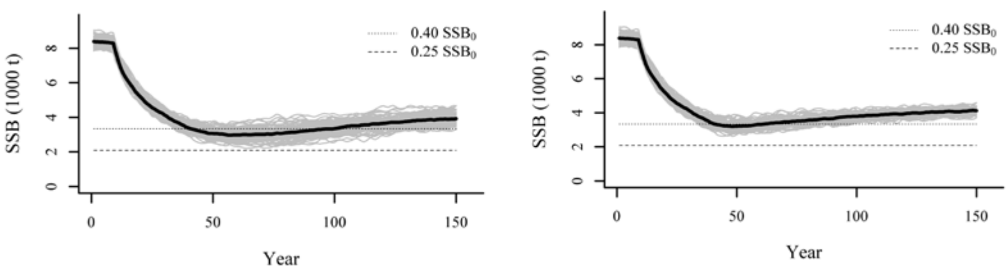


Figure 37 HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, 100 simulations. Left quadrennial, right biannual adjustment of the TAC.

5.2.7 Testing a 2-over-5 rule

We compared the performance of the HCR combining mean length and CPUE index using a 2-over-3 rule with a 2-over-5 rule Figure 38. We find the 2-over-5 rule leads to slightly faster recovery (median SSB above the 40%SPR threshold), lower risk to fall below biomass thresholds. In comparison the lowest observed SSB in the time-series is higher than with a 2-over-3 rule. This is due to the stronger reduction in TAC with a 2-over-5 rule when the CPUE is decreasing over multiple years.

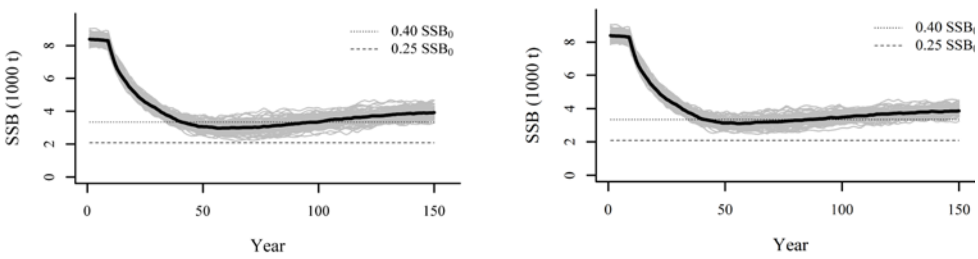


Figure 38. HCR combined $\bar{L}/L_{F=M}$ and CPUE, constraint (-25%, 15%), $L_{50\%}$=450, 100 simulations. CPUE index: Left panel 2-over-3 rule, Right panel 2-over-5 rule.

5.2.8 Alternative selectivity (dome-shaped)

At dome-shaped selectivity largest individuals are subject to lower/no fishing mortality (Figure 39). This can be due to spatial segregation of life stages and limitation of fisheries distribution in space.

With dome-shaped selectivity larger individuals are missing in the catch and mean length is lower than expected for asymptotic selectivity. The HCRs will have lower risk to fall below biomass thresholds as the lower mean length in the catch will trigger a downward TAC adjustment, using reference points derived for asymptotic selectivity. It is recommended to compare survey and commercial catch length distributions and their indicators. Large differences in particular in the length of the largest 5% can indicate a dome-shaped selectivity.

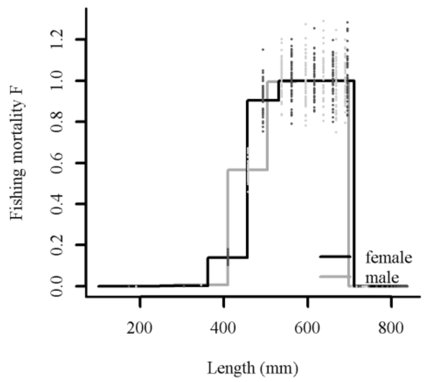


Figure 39. Fishing selectivity (f=1, L_c=450, dome-shaped selectivity F=0 for length classes >700 mm).

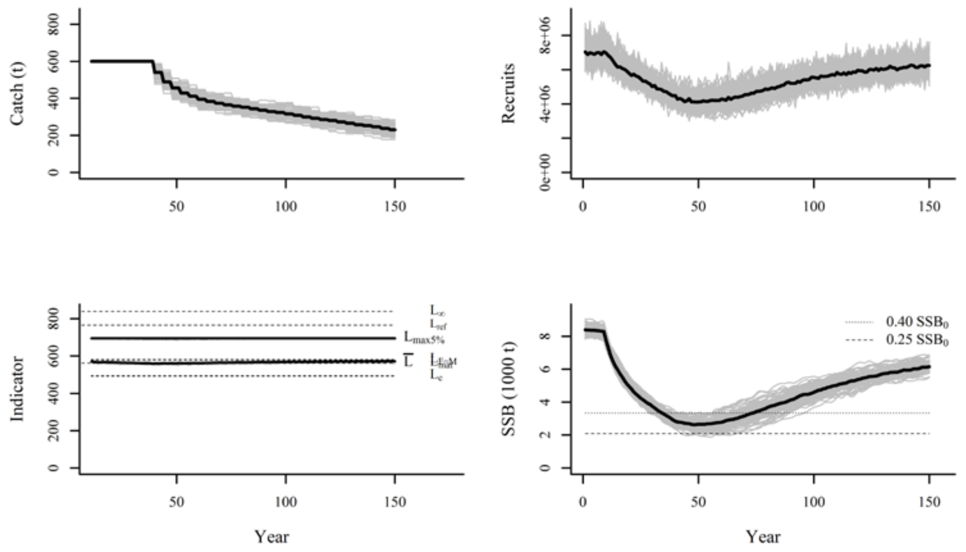


Figure 40. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, 100 simulations, dome-shaped selectivity.

5.2.9 Testing uncertainty in CPUE index

There often is uncertainty on the CPUE index (survey, commercial CPUE). We compare the performance of HCRs with implementation of an error on CPUE. We find a higher variability of results. A highly asymmetric constraint on TAC change (-25%, 5%) reduces the variability (Figure 41). With a tighter upper constraint (5%), it can be avoided that the TAC is increased a lot, which protects against false assumptions if the actual stock status would suggest a TAC reduction. An unnecessary reduction in TAC due to error and the wider negative constraint makes this HCR more precautionary by lowering the risk of falling below biomass thresholds.

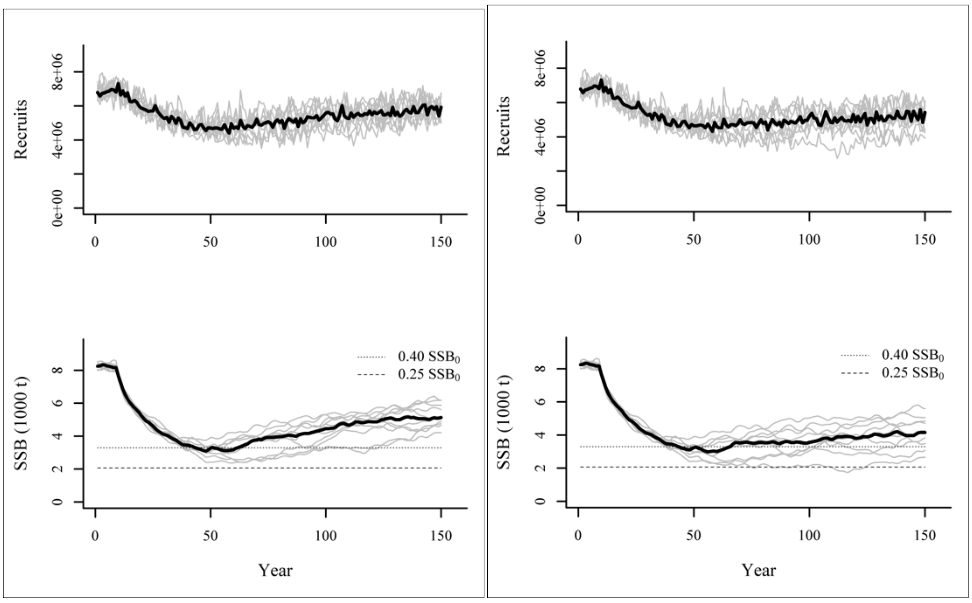


Figure 41. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), $L_{50\%}$=450, 100 simulations. Left panels constraint (-25%, 5%), right panels constraint (-25%, 15%).

5.3 Conclusions

We tested HCRs using length-based indicators mean length for the management of an elasmobranch stock. Stocks such as Cuckoo ray, with an M/k ratio larger than 1 are expected to exhibit enough truncation in catch length distributions in response to over-exploitation to allow for an application of the length-based indicators to monitor stock status (ICES, 2018a). Both mature and immature Cuckoo rays are harvested ($L_c<L_{mat}$). A HCR based on the mean length and $L_{F=M}$ does not perform well when length at first capture is well below maturation size (Jardim *et al.*, 2015). This is due to the fact that the analytical reference point $L_{F=M}$ is independent of maturation schedule, depends on the assumption of constant recruitment and F=M. Due to the relatively large maturation size, the longer generation time and relatively low fecundity, the management of Elasmobranch stock (even with high M/k) may be more challenging. If the selectivity cannot be adjusted (for example for bycatch species), the performance of HCRs can be improved by combining the length-based indicator with an index of stock abundance (CPUE) of the shape:

$$\mathrm{TAC}_{t+1} = \mathrm{TAC}_{\mathrm{current}} \times \mathrm{r} \times \mathrm{f}, \qquad \text{(Equation 1)}$$

to adjust catches C, with r representing the stock index CPUE trend and f being the mean length ratio $\bar{\mathrm{L}}/\mathrm{L}_{\mathrm{F=M}}$.

The CPUE trends can be used in the HCR in a 2-over-3 rule ((average of stock size index in the two most recent years)/(average of stock size index in the three preceding years). Alternatively, we found better performance of a HCR using the CPUE index in a 2-over-5 rule.

The number of recruits in elasmobranch stocks is closely linked to the number of mature females. Therefore, the potential of very large cohorts when SSB is low, and the recovery of a stock is closely linked to the abundance of mature females. We tested the HCRs using a stock–recruitment relationship where the number of recruits strongly decreases with SSB. The HCR combining mean length and CPUE index showed a low risk of stock collapse, even if immature individuals are subject to fishing. The HCR is relatively robust against misspecification of a parameter. However, if available life-history parameters estimate vary for a stock, the combination delivering the highest reference point $L_{F=M}$ will be most precautionary in preventing stock collapse. For example, underestimating natural mortality M, which is often uncertain, results in a higher length-based reference point and a more precautionary HCR. The reference point $L_{F=M}$ is sensitive to the estimation of L_c and assumes a knife-edge selectivity. WKSHARK4 suggested to use the mode of the catch length distribution approximate L_c, rather than the length at 50% of the mode (ICES, 2018c). The reference point $L_{F=M}$ increases, ignoring exploitation on individuals smaller than L_c, and the risk of collapse can be reduced.

For sexually dimorphic stocks, it is suggested to use the life-history characteristics of the larger sex (in terms of larger L_∞) for reference point calculation. This will result in higher reference points and lower risk of stock collapse. The larger sex will be subject to stronger truncation in length distribution with in exploitation, if both sexes are fished equally. The indicator calculation can be done combined sexes or females only. Using combined sex to calculate indicator values can lead to slightly lower indicators than using females only and is preferred especially at low sample size.

To estimate the mean length in the sampled catch, length samples should be unbiased representing the fishery on the stock. The number of individuals sampled from commercial catches can affect the variability of the mean length estimator at very low sample sizes. High variability of the indicator increases the risk of collapse. Since the mean length is less affected by the presence of rare size classes and the HCR combines the indicator with stock index, the performance of the HCR is not affected as long as the number of sampled individuals from the most abundant size class is well above 100 (random sampling).

Dome-shaped selectivity can affect the evaluation of stock status based on length-based indicators. A comparison of survey and commercial catch length distributions can help to investigate the selectivity pattern. A lack of large size classes in catch length distributions but presence in survey length distributions can indicate a dome-shaped selectivity (at sufficient sample size). Spatial segregation of life stages can lead to dome-shaped selectivity. It should be noted that both survey and fishery may not cover the full range of the species distribution, which makes identification of selectivity pattern difficult. At actual dome-shaped selectivity but assumption of asymptotic selectivity for the reference point, will lead to overestimation of exploitation level based on length-based indicators. A decreasing trend in indicators can point to a truncation in population size distribution and a downward trend in stock abundance. However, constant indicators cannot exclude decreasing stock size, of selectivity is dome-shaped. In this case, the proposed HCRs are precautionary by reducing the risk of stock collapse but may lead to unrealistically low TAC.

To summarize:

1) If possible, manage fishery with $L_c > L_{mat}$.
2) It is recommended to use a biennial rather than a quadrennial assessment to allow for a faster reduction in TAC when the stock is overexploited.
3) Stocks with high ratios of M/k>1 can use length-based indicators to formulate HCRs, which rely on sufficient observable truncation in the right-hand tail of length distributions in response to fishing mortality (ICES, WKLIFE 2017).
4) Combined HCR, $\bar{L}/L_{F=M}$ and CPUE (2o3 or preferable 2o5 rule), reduces the risk to collapse following fishing $L_c < L_{mat}$, life-history parameter misspecification, low sampling level of length distribution.
5) $L_{F=M}$ should be calculated using best available life-history information. Avoid underestimating the reference point (for example by overestimating M or underestimating L_c). For sexually dimorphic stocks, it is recommended to use life-history parameters for the larger sex (Cuckoo rays: females) leading to the higher reference point.
6) For elasmobranchs the indicator mean length above L_c (defined as the mode of the catch length distribution can be used in a HCR. The LBI ratio (component f) used in HCR should be calculated using an average of mean length (of the most recent years) to reduce the effect of interannual variability of length distributions.
7) Asymmetric constraint on TAC change (such as -25%, 5%) reduces the risk to collapse due to error in the CPUE index.
8) These recommendations is given for assumed asymptotic fishing selectivity. The selectivity patterns of the fishery should be evaluated by comparing

commercial catch length distributions to survey catch length distributions (if available).

5.4 Future directions

Further work is required to optimize an HCR also in the case of dome-shaped selectivity patterns in the fishery. The assumptions on fisheries behaviour should be further investigated, with respect to the effect of interannual variability or trends in fisheries selectivity (L_c). The performance of the HCR on other elasmobranchs stocks is recommended as life histories can vary widely. Further evaluations considering a weighing of HCR components can help to improve HCR performance.

5.5 References

Cailliet, G. M., Musick, J. A., Simpfendorfer, C. A., and Stevens, J. D. 2005. Chapter 3 Ecology and Life History Characteristics of Chondrichthyan Fish. *In* Sharks, Rays and Chimaeras: The Status of Chodrichtyan fishes, Satus Survey, p. 461pp. Ed. by S. L. Fowler, R. D. Cavanagh, M. Camhi, G. H. Burgess, G. Cailliet, S. V. Fordham, C. A. Simpfendorfer *et al.* IUCN/Shark Specialist Group, IUCN, Gland, Switzerland and Cambridge, UK.

Dulvy, N. K., Metcalfe, J. D., Glanville, J., Pawson, M. G., and Reynolds, J. D. 2000. Fishery stability, local extinctions, and shifts in community structure in skates. Conservation Biology, 14: 283–293.

Frisk, M. G., Miller, T. J., and Fogarty, M. J. 2001. Estimation and analysis of biological parameters in elasmobranch fishes: a comparative life history study. Canadian Journal of Fisheries and Aquatic Sciences, 58: 969–981.

Gallagher, J., Jeal, F., and Nolan, C. P. 2005. An investigation of the Irish ray fishery in ICES Divisions VIIa and VIIg. Journal of Northwest Atlantic Fisheries Science, 35: 1:13.

García, V. B., Lucifora, L. O., and Myers, R. A. 2008. The importance of habitat and life history to extinction risk in sharks, skates, rays and chimaeras. Proceedings of the Royal Society B: Biological Sciences, 275: 83–89.

Hordyk, A., Ono, K., Sainsbury, K., Loneragan, N., and Prince, J. 2015. Some explorations of the life history ratios to describe length composition, spawning-per-recruit, and the spawning potential ratio. ICES Journal of Marine Science, 72: 204–216.

ICES. 2015. Report of the Workshop on the development of quantitative assessment methodologies based on LIFE-history traits, exploitation characteristics and other relevant parameters for data-limited stocks (WKLIFE V) 5–9 October 2015 Lisbon, Portugal. ICES CM 2015/ACOM:56: 1–157.

ICES. 2016. Report of the Workshop on the development of quantitative assessment methodologies based on LIFE-history traits, exploitation characteristics and other relevant parameters for data-limited stocks categories 3–6 (WKLIFE VI) 3–7 October 2016 Lisbon, Portugal. ICES CM 2016 / ACOM:59: 1–106.

ICES. 2017. Report of the Working Group on Elasmobranchs (WGEF), 31 May–7 June 2017, Lisbon, Portugal. ICES CM 2017/ACOM: 16: 1018 pp.

ICES. 2018a. Report from the Workshop on the development of quantitative assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for stocks in categories 3–6 (WKLIFE), 2–6 October 2017, Lisbon, Portugal. ICES CM 2017/ACOM: 43: 221 pp.

ICES. 2018b. Report of the Working Group on Elasmobranch Fishes (WGEF), 19–28 June 2018, Lisbon, Portugal. ICES CM 2018/ACOM: 16: 1306 pp.

ICES. 2018c. Report of the Workshop on Length-Based Indicators and Reference Points for Elasmobranchs (WKSHARK4), 6–9 February 2018, Ifremer, Nantes (France). ICES CM/ACOM: 37: 112pp.

ICES. 2012. Report of the Workshop to finalise the ICES data-limited Stocks (DLS) methodologies documentation in an operational form for the 2013 advice season and to make recommendations on target categories for data-limited stocks (WKLIFE II), 20–22 November 2012, Copenhagen, Denmark. ICES CM2012/ACOM:79: 1–46.

Jardim, E., Azevedo, M., and Brites, N. M. 2015. Harvest control rules for data-limited stocks using length-based reference points and survey biomass indices. Fisheries Research, 171: 12–19 pp.

Jennings, S., Kaiser, M. J., and Reynolds, J. D. 2001. Marine Fisheries Ecology, Blackwell Publishing.

Maia, C., Erzini, K., Serra-Pereira, B., and Figueiredo, I. 2012. Reproductive biology of cuckoo ray *Leucoraja naevus*. Journal of Fish Biology, 81: 1285–1296.

Miethe, T., and Dobby, H. 2015. Selection of length-based indicators for shellfish stocks and fisheries. Working Document in Report of the Workshop on the development of quantitative assessment methodologies based on LIFE-history traits, exploitation characteristics and other relevant parameters for data-limited stocks (WKLIFE V) 5–9 October 2015 Lisbon, Portugal, ICES CM 2015/ACOM:56.

Miethe, T., and Dobby, H. 2016. Testing length-based indicators in harvest control rules (HCR) for shellfish stocks and fisheries. Working Document in Report of the ICES workshop on the development of quantitative assessment methodologies based on life-history traits, exploitation characteristics and other relevant parameters for data-limited stocks category 3–6 (WKLIFE VI), ICES CM 2016/ACOM:59: 58–76.

Miethe, T., Dobby, H., and McLay, A. 2016. The use of indicators for shellfish stocks and fisheries: a literature review. Scottish Marine and Freshwater Science, 7: 1–76.

Pauly, D. 1980. On the interrelationships between natural mortality, growth parameters, and mean environmental temperature in 175 fish stocks. J du Conseil Int pour l'Exploration de la Mer, 39.

Smith, S. E., Au, D. W., and Show, C. 1998. Intrinsic rebound potentials of 26 species of Pacific sharks. Marine and Freshwater Research, 49: 663–678.

Stevens, J. D., Bonfil, R., Dulvy, N. K., and Walker, P. A. 2000. The effects of fishing on sharks, rays, and chimaeras (chondrichthyans), and the implications for marine ecosystems. ICES Journal of Marine Science, 57: 476–494.

Taylor, I. G., Gertseva, V., Methot, R. D., and Maunder, M. N. 2013. A stock–recruitment relationship based on pre-recruit survival, illustrated with application to spiny dogfish shark. Fisheries Research, 142: 15–21.

Then, A. Y., Hoenig, J. M., Hall, N. G., and Hewitt, D. A. 2015. Evaluating the predictive performance of empirical estimators of natural mortality rate using information on over 200 fish species. ICES Journal of Marine Science, 72: 82–92.

6 Future directions for DLS stocks

6.1 Links with ICES WGBIOP

The approaches used within WKLIFE rely upon life-history traits and as ICES progresses towards providing quantitative catch advice and forecasts, it is important that agreed parameter values are used for the stocks that ICES provides advice for.

In previous meetings of WKLIFE, there have been discussions about maintaining links with ICES WGBIOP and in the 2017 report of the WGBIOP meeting the following statement appears:

WGBIOP aim to review the current estimates of life-history parameters required for models to calculate MSY proxies as used by WKPROXY and subsequent WKLIFE meetings. These are: von Bertalanffy growth function Linf (also referred to as L∞) (mm), von Bertalanffy k (yr^{-1}), Length–weight a, Length–weight b, Natural mortality M (yr^{-1}), and Length-at-maturity (mm). We will look to liaise with WKLIFE scientists to work towards documenting sources of these estimates and, through our other ToRs, continue work on improving the quality of the underlying data.

The need remains to identify values for these parameters so that they can be used in further simulations and the continued development of advice rules within WKLIFE.

6.2 ICES ASC 2020 theme session proposal

During this year's ICES Annual Science Conference (ASC) and this meeting of WKLIFE, it was mooted that a theme session be proposed for the ICES ASC in 2020; signifying ten years of development of data-limited methods within the ICES community. The following proposal captures this intention.

Title and conveners

Advances in data-limited approaches; their evolution, achievements and future prospects

- Manuela Azevedo (Portugal), John Hoenig (USA), Carl O'Brien (UK)

Description

Fish and shellfish stocks without full analytical assessments have often been ignored by science and management, thus limiting their conservation potential as science has been deemed uninformative for decision-making. The International Council for the Exploration of the Sea (ICES) provides advice for over 200 stocks in the North Atlantic; however, more than half of these stocks are data-limited and the usefulness of scientific advice questionable. In 2011, ICES began developing a set of precautionary methods for data-limited stocks in an effort to utilize the data and information available to aid policy-makers' move towards sustainable exploitation of fisheries. Using these methods, ICES provided quantitative advice to policy-makers for more than 100 of these stocks in 2012. This marked a major step forward in the management and conservation of many vulnerable stocks and species, including sharks and commercially exploited species such as flounder, brill and pollack. The methods' framework categorizes stocks by the information available and provides an assessment methodology for each case, reflecting the decreasing availability of data and greater uncertainty in stock status. The underlying principle applies more precaution in more uncertain situations. Consequently, the less information available, the more conservative the advice. This theme session will reflect upon the ICES approach to data-limited stock assessment, including the methods' framework, details of its implementation and evolution, and its influence on TAC and quota decisions in the North Atlantic.

Further developments of the approach and ongoing science will be discussed, together with the relative importance of life-history parameters and their impact on management measures.

Suggested theme session format

The session would start with a keynote presentation by the co-chairs of WKLIFE outlining the evolution of goals within ICES, achievements and lessons learned, and the impacts within both science and management. WKLIFE has provided guidance to institutions including Commissions, Governments and academia about how to handle the past emerging challenges of data-limited situations. Future challenges are likely to require data-limited guidance on multispecies management, ecosystem interactions, evolving environmental conditions and sociological factors. Presentations in all these areas will be welcomed.

Annex 1: Working document -Model description for testing catch rules for the elasmobranch Cuckoo ray (*Leucoraja naevus*) and additional result figures

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Population model

We construct a length-based sex-structured population model to test harvest control rules for Cuckoo ray (*Leucoraja naevus*). For this purpose, we use a length-based model with length classes of varying bin width such that individuals grow into the next length class within a single time-step, as described by Andrews *et al.* (2006), Gurney *et al.* (2007) and Speirs *et al.* (2010). This results in a parsimonious number of length classes for each sex. The use of very small time-steps or many narrow length classes can thereby be avoided, improving computational efficiency.

In the model, growth occurs instantaneously at the end of each time-step and is irreversible. To incorporate variability of growth into the model, it is assumed that only a fraction, p, of individuals in a length class grows to the next size class within any time-step and the remaining fraction, (1-p), of individuals stay at their current size for another time-step(Gurney *et al.*, 2007; Speirs *et al.*, 2010). A value of p=0.9 is selected, which limits the variability allowing only 10% of individuals to remain in their current length class after one time-step while keeping the general growth pattern close to the respective von Bertalanffy growth equation.

In order to create the length bins, a development index (q) is defined for each sex as a function of length L (Gurney *et al.*, 2007; Speirs *et al.*, 2010):

$$q \equiv -\ln\left(\frac{L_\infty - L}{L_\infty - L_{min}}\right), \quad (2)$$

where L_∞ is the respective asymptotic length. At the minimum length at which recruits are assumed to enter the population, L_{min}, q is zero. Following von Bertalanffy growth, q increases linearly with length and tends to infinity as the individual length approaches L_∞. A finite q_{max} can be calculated for an arbitrary maximum length L_{max}, which is slightly less than L_∞. All length classes are of fixed q width (Δq) but varying length bin width: classes are wider (in length) early in life when the individual growth rate is high and decrease as growth slows later in life, when individuals approach asymptotic size.

To ensure growth follows the von Bertalanffy growth equation, it can be shown that in the unexploited population, the increment Δq is set with respect to the growth rate k, growth variability coefficient p and the time-stepΔt of the model (Speirs *et al.*, 2010):

$$\Delta q = \frac{k\Delta t}{p}. \quad (3)$$

The number of length classes for each sex (n_m, n_f) can then be calculated using the respective sex-specific growth parameters:

$$n_{sex} = \frac{q_{max}}{\Delta q} \quad (4)$$

The total number of length classes in the model, n, is the sum of male, n_m, and female length classes, n_f. The left-hand (lower) boundary of each length class i in terms of the development index is:

$$L_i = L_\infty - (L_\infty - L_{min})\, e^{(-(i-1)\Delta q)} \tag{5}$$

using L_∞ and Δq for the respective sex. The midpoint of each length class, l_i, is calculated as the mean length of the lower boundary (Equation 5) and the lower boundary of the next larger length class. For the maximum length class of each sex, the respective L_∞ is used as the upper boundary to calculate the midpoint.

The length classes are constructed under the assumption of size-independent mortality. The approach is robust to size-dependent mortality, which directly affects the size distribution while the size distribution of a cohort at any age changes relatively little (Gurney *et al.*, 2007).

Using $N_{i,t}$ to denote the number of individual in length class i at time t, the population dynamics are expressed in difference equations for two sexes and n length classes:

$$N_{i,t+1} = \begin{cases} e^{-(M+F_{i,t})}(1-p)N_{i,t} + \frac{1}{2}R_{t+1} & \text{for } i = 1 \text{ and } i = (n_m + 1) \\ e^{-(M+F_{i-1,t})}pN_{i-1,t} + e^{-(M+F_{i,t})}(1-p)N_{i,t} & \text{for } 1 < i < n_m \text{ and } (n_m+1) < i < n_f \\ e^{-(M+F_{i-1,t})}pN_{i-1,t} & \text{for } i = n_m \text{ and } i = n_f \end{cases} \tag{6}$$

where R_{t+1} is total recruitment at time t+1 and assumed to be split equally between males and females (entering only the smallest length class).

Mortality

The population is subject to both fishing and natural mortality, which occur simultaneously and continuously through time. Natural mortality is assumed to be constant over time, length and for both sexes. Natural mortality is estimated using the length-based updated Pauly estimator recommended by Then *et al.* (2015), corrected by Then *et al.* (2018), using L_∞ of the larger sex (female):

$$M = 4.118k^{0.73}(L_\infty/10)^{-0.33}(L_\infty \text{ in mm}) \tag{7}$$

Fishing mortality at time t and length class i, $F_{i,t}$, is assumed to be separable and can be written as the product of a length-dependent selectivity ogive (logistic curve) and a time-dependent component, f_t, related to the level of fishing effort in the fisheries:

$$F_{i,t} = f_t \frac{1}{1+e^{-v(l_i - L_{50\%})}} e^{\varepsilon 1_{i,t}} \tag{8}$$

where $L_{50\%}$ is the length at 50% retention, and v is a constant describing the steepness of the selectivity ogive. A lognormal error is included to allow for variability of fishing mortality, with $\varepsilon 1_{i,t}$ being normally distributed with $N(0, \sigma_F^2)$.

Catch in numbers by length class i at time t is calculated according to the Baranov catch equation:

$$C_{i,t} = \frac{F_{i,t}}{M+F_{i,t}}\left(1 - e^{-(M+F_{i,t})}\right)N_{i,t} \tag{9}$$

and total yield (assuming zero discards) are given by:

$$Y_t = \sum_{i=1}^{n} w_i\, C_{i,t} \tag{10}$$

Maturity and SSB

In this model, the smallest length class includes individuals from 100 mm length for either sex. Mature individuals produce offspring at the beginning of the time-step and only in the following time-step do recruits enter the smallest length class of the population. The maturity ogive is defined as a logistic function with an inflection point around the sex-specific length at 50% maturity, L_{mat} and calculated for the midpoint of each length class l_i:

$$Mat_i = \frac{1}{1+e^{-u(l_i-L_{mat})}} \tag{11}$$

Spawning–stock biomass is calculated as the sum of individual weights of all mature individuals in the stock:

$$SSB_t = \sum_{i=1}^{n} Mat_i N_{i,t} a l_i^b \tag{12}$$

The individual weights-at-length are calculated using sex-specific exponential length–weight relationships with parameters a and b, which are constant over time.

Recruitment

Recruitment is related to the number of mature females in the previous year and is assumed to follow a Beverton–Holt relationship with multiplicative lognormal error:

$$R_{t+1} = \frac{cNMat_t}{1+dNMat_t} e^{\left(\varepsilon 2_{t+1} - \frac{\sigma_R^2}{2}\right)} \tag{13}$$

The error $\varepsilon 2_{t+1}$ is normally distributed with N(0, σ_R^2) and is combined with a bias correction term (Thorson and Kristensen, 2016). The specific life-history parameters used in the model are listed in Table 1. We choose parameters to relate numbers of females (rather than SSB) to recruitment with parameter values, to result in a relatively strong reduction in recruitment with decreasing SSB as expected for elasmobranchs.

Alternatively, we try out a different relationship suggested for elasmobranchs stocks (Taylor *et al.*, 2013). A survival function determines prerecruit survival:

$$R_{t+1} = S_y B_y = S_y NMat_t, \tag{14}$$

where B_y is the spawning output (total number of eggs calculated from number of mature females times fecundity).

$$S_y = \exp\left(-z_0 + (z_0 - z_{min})\left(1 - \left(\frac{B_y}{B_0}\right)^{\beta}\right)\right), \quad (15)$$

where $z_{min} = -z_0(1 - z_{frac})$ and $z_0 = -\log(R_0/B_0)$, $z_{frac} = 0.1$, $\beta = 1$, $B_0 = 30\,000\,000$, $R_0 = 0.1B_0$, fecundity=60.

The number of surviving recruits are split equally between males and females (entering only the smallest length class).

Reference points

The derivation of the reference point for $\bar{L}$, $L_{F=M}$, requires the assumptions that the population is at equilibrium with individuals following deterministic von Bertalanffy growth, natural mortality is independent of size, fishing mortality occurs with knife-edged selectivity. An analytical expression for the calculation of the reference point $L_{F=M}$ was presented by Jardim *et al.* (2015), with $\theta = \frac{k}{M}$ and $\gamma = \frac{F}{M} = 1$:

$$L_{F=\gamma M, k=\theta M} = \frac{\theta L_\infty + (\gamma+1)L_c}{\theta+\gamma+1} \quad (16)$$

The reference point depends on L_c and stock-specific biological parameters of L_∞, M, and k (females, Table 1). The respective values of L_c are calculated from the 'sampled' catch-at-length data generated with the simulation model. Alternative expected values for the mean length in the catch can be calculated for any given F/M.

For comparison we calculate $F_{40\%}$ and the respective mean length in the catch using analytical models. The standardized von Bertalanffy growth equation are used to calculate the expected non-dimensional length distribution in the stock and in the catch, under the assumptions that the population is at equilibrium with individuals following deterministic von Bertalanffy growth, natural mortality independent of size and fishing mortality with knife-edged fishery selectivity (Miethe *et al.*, in prep.):

The theoretical mean length in the catch of an unexploited stock is calculated by setting F=0 in equation 16.

Similarly, we can calculate the mean length at $F_{40\%}$, which satisfies SPR=0.4:

$$SPR = \begin{cases} \dfrac{\int_{t_{mat}}^{\infty} e^{Ft_c} e^{-(F+M)t} \tilde{L}^b dt}{\int_{t_{mat}}^{\infty} e^{-Mt} \tilde{L}^b dt} & t_{mat} < t_c \\ \dfrac{\int_{t_{mat}}^{t_c} e^{-Mt} \tilde{L}^b dt + \int_{t_c}^{\infty} e^{Ft_c} e^{-(F+M)t} \tilde{L}^b dt}{\int_{t_{mat}}^{\infty} e^{-Mt} \tilde{L}^b dt} & t_{mat} \geq t_c \end{cases} \quad (17)$$

where $\tilde{L} = \frac{L}{L_\infty}$ is the standardized length and t_c and t_{mat} are calculated from the respective standardized lengths $\tilde{L}_c$ and $\tilde{L}_{mat}$:

$$t = \frac{-\ln(1-\tilde{L})}{k} \quad (18)$$

Reference points are calculated for wide range of values of L_c.

Simulation scenarios and harvest control rules

To evaluate the performance of indicator-based HCRs, we make use of a MSE framework and consider a number of different scenarios with respect to selectivity of the fishery, natural mortality and reference points. Robustness of HCRs to selectivity is investigated through alternative scenarios with regard to $L_{50\%}$ of the selectivity ogive. We run scenarios with an $L_{50\%}$ of 450 mm (i.e. smaller than L_{mat}) and with $L_{50\%}$ of 600 mm (greater than L_{mat}). As length-based indicators we calculate the mean length in the catch and the mean length of the largest 5% in the catch, $L_{max5\%}$(Probst *et al.*, 2013).

Each scenario is simulated 1000 times. The simulations are run for a total of 150 years to allow observation of the full recovery cycle with TAC (total allowable catch) management using the HCR. All simulations are carried out in R (R Core Team, 2017). Each simulation is initiated with a stock at the unexploited equilibrium and with stochastic recruitment. After ten years without exploitation, the fishery is assumed to begin, initially with a constant catch (TAC) at a level which causes the stock to be overexploited. Then from year 40 onwards when a TAC management is implemented, catch is defined by an indicator-based HCR.

Two HCRs, which update the TAC on a quadrennial basis, are tested within the MSE framework. The HCRs are based on mean length and $L_{F=M}$ reference points. In each HCR, the future TAC is assumed to be proportional to the current TAC (year t) and a time-dependent multiplier, calculated as the ratio of the average of the length-based indicator (LBI) in the previous four years to the respective reference point:

$$TAC_{t+1} = \frac{1}{4}\sum_{k=t-4}^{t-1}\frac{\bar{L}_k}{L_{F=M}} \times TAC_t \qquad \text{where } t = 40, 44, 48, \tag{19}$$

The initial TAC for time 10 to 40 is constant. For the simulation of an overexploited stock and given selectivity ogive, the initial TAC is set to a value to allow for median SSB to fall below 40%SPR in the first 40 years of the simulation.

The annual TAC change after t=40 is limited to ±15 %. Truncation of the length distribution will first be visible in the larger sex (in this case females) if both sexes are exploited equally. Therefore the HCRs are based only on the female indicators and reference points. The reference points are derived using analytical models as detailed in the following Section 2.1.

Alternatively, we test for the effect of a biennial assessment and asymmetric constraints on TAC (-25%, 15% and -25%, 5%) change.

We test a combined HCR which uses the LBI ratio and a stock index based on CPUE to adjust catches:

$$TAC_{t+1} = \frac{1}{4}\sum_{k=t-4}^{t-1}\frac{\bar{L}_k}{L_{F=M}} \times \frac{CPUE_2}{CPUE_3} \times TAC_t \qquad \text{where } t = 40, 44, 48, \tag{20}$$

CPUE is calculated as the ratio of catch and fishing mortality level from the model output. In a 2-over-3 rule the ratio of the mean CPUE in the most recent two years and the previous three years is calculated. Instead of a 2-over-3 rule, we compare results to those using a 2-over-5 rule (ICES, 2018a).

Uncertainty in the CPUE index is included using a lognormal error $\varepsilon 3_t$ with $N(0,\sigma_{CPUE})$.

$$CPUE_t = \frac{Yield_t}{f_t \times e^{\varepsilon 3_t}} \tag{21}$$

To test misspecification in M or M/k, reference points are calculated with ±10% error and HCRs evaluated.

For a given TAC, the annual fishing mortality multiplier, f_t (equation 8), is derived by numerically solving equations8–10. The value of f_t is limited to a maximum of 6.0, to avoid infinite values of fishing mortality as the population declines to zero. The numerically derived f_t is then used to calculate catch-at-length data and project the population for the next time-step. To account for observation error introduced through the sampling process, 'sampled' catch-at-length data are generated by randomly selecting 1% of the total number of individuals in the catch from the model-simulated empirical catch–length distribution.

Alternatively, we randomly use a range of percentages between 0.01% and 5% to select from the total number of individuals in the catch from the model-simulated empirical catch length distribution to assess the effect of sampling size on performance of HCRs.

Length-based indicators, $L_{max5\%}$ and $\bar{L}$, are calculated from the 'sampled' catch-at-length data for use in the HCR. $\bar{L}$ is calculated as the mean length of individuals larger than L_c (the length at first capture), $\bar{L}$ is calculated as the mean length of individuals larger than L_c (the length at first capture), the length at which the frequency reaches 50% of the mode on the left hand side of the distribution (Jennings *et al.*, 2001; ICES, WKLIFE 2012). L_c of the 'sampled' catches is then equivalent to the $L_{50\%}$of the selectivity ogive, and it corresponds to L_c in the analytical model with knife-edge selectivity to determine the reference points. Alternatively, we run scenarios with L_c calculated as the mode of the length distribution as suggested by ICES (2018b).

We calculate the annual probability of being below 0.25 SSB_0 (25% of unexploited spawning–stock biomass) and 0.4 SSB_0. The risk of falling below 0.25 SSB_0 and 0.4 SSB_0 after implementation of the HCR (year 40) is determined for each ten year period as the maximum annual probability of being below the respective SSB threshold.

Table and Figures

Table A 1. Parameters *L. Naevus*, using life-history characteristics for Irish Sea stock.

Description	parameter	value	unit	reference
Von Bertalanffy growth	K (male)	0.294		Gallagher *et al.* (2005)
	K (female)	0.197		
	L_∞ (male)	746	mm	
	L_∞ (female)	839	mm	
Natural mortality	M (male)	0.406		Then *et al.* (2015)
	M (female)	0.292		
Life-history ratio M/K	M/K (male)	1.38		
	M/K (female)	1.48		
Maximum length to determine number of classes	L_{max} (male)	745.5	mm	0.5 below L_∞
	L_{max} (female)	838.5	mm	
Minimum modelled length	L_{min}	100	mm	ICES, 2004
Growth variability constant	p	0.9		
Times step	Δt	1		
Length at 50% retention	$L_{50\%}$	450	mm	
Selectivity ogive constant	v	0.07		
Standard deviation of $\varepsilon 1_{t,i}$ (fishing mortality)	σ_F	0.1		
Standard deviation of $\varepsilon 3_{t,i}$ (CPUE)	σ_{CPUE}	0.1		
Length–weight relationship	a′ (male)	0.0041	g cm^{-b}	McCully *et al.* (2012) to mm $a=a'10^{-b}$
	a′ (female)	0.0035	g cm^{-b}	
	b (male)	3.105		
	b (female)	3.147		
Size at 50% maturity	L_{mat} (males)	568.7	mm	Gallagher *et al.* (2005)
	L_{mat} (females)	561.6	mm	
Maturity ogive constant	u	0.06		
Recruitment relationship	c	6		
	d	$6*10^{-7}$		
Standard deviation of ε_{2t+1} (fecundity)	σ_{Rec}	0.08		

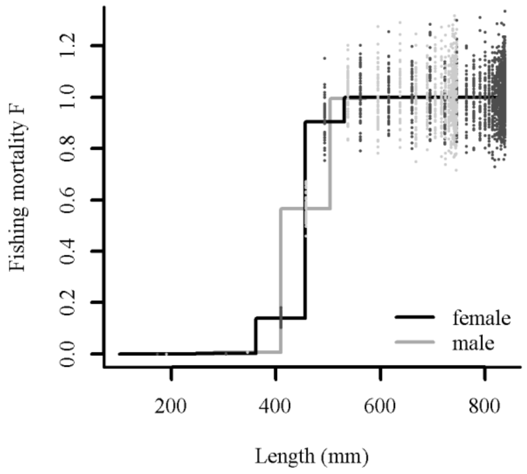

Figure A 1. Fishing selectivity (f=1, L_c=450, asymptotic).

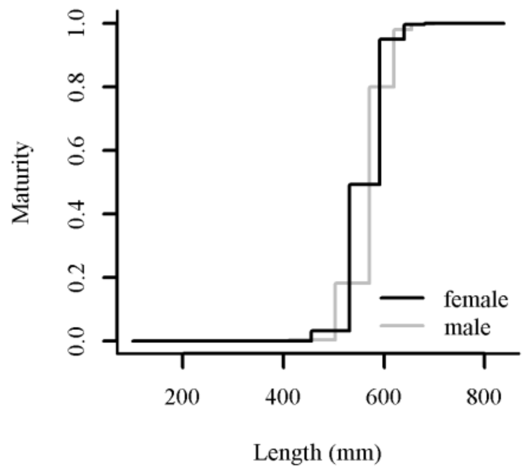

Figure A 2. Maturity ogive for male and female Cuckoo ray.

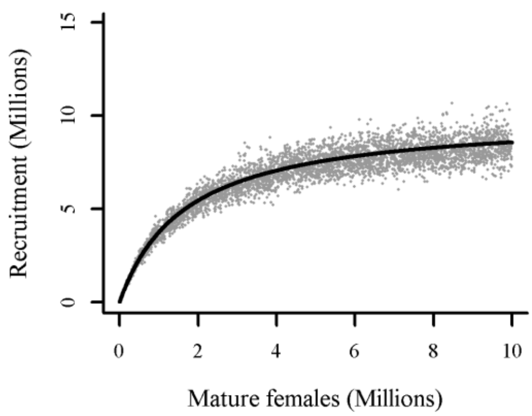

Figure A 3. Spawner–recruitment relationship (Beverton–Holt), at unexploited equilibrium around 6.4 Million recruits and 4.5 Million mature females (strong reduction in recruitment with decreasing SSB).

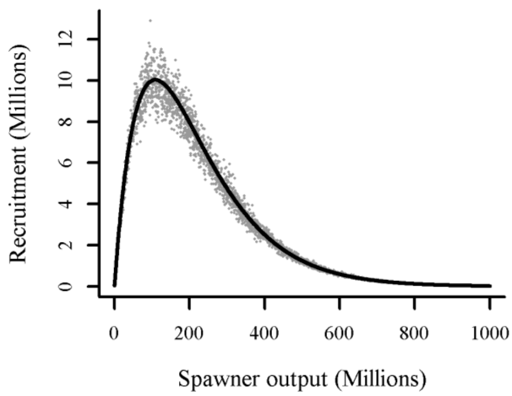

Figure A 4. Spawner output-recruitment relationship (Taylor *et al.*), at unexploited equilibrium around 6 Million recruits (left side of the function used in simulations).

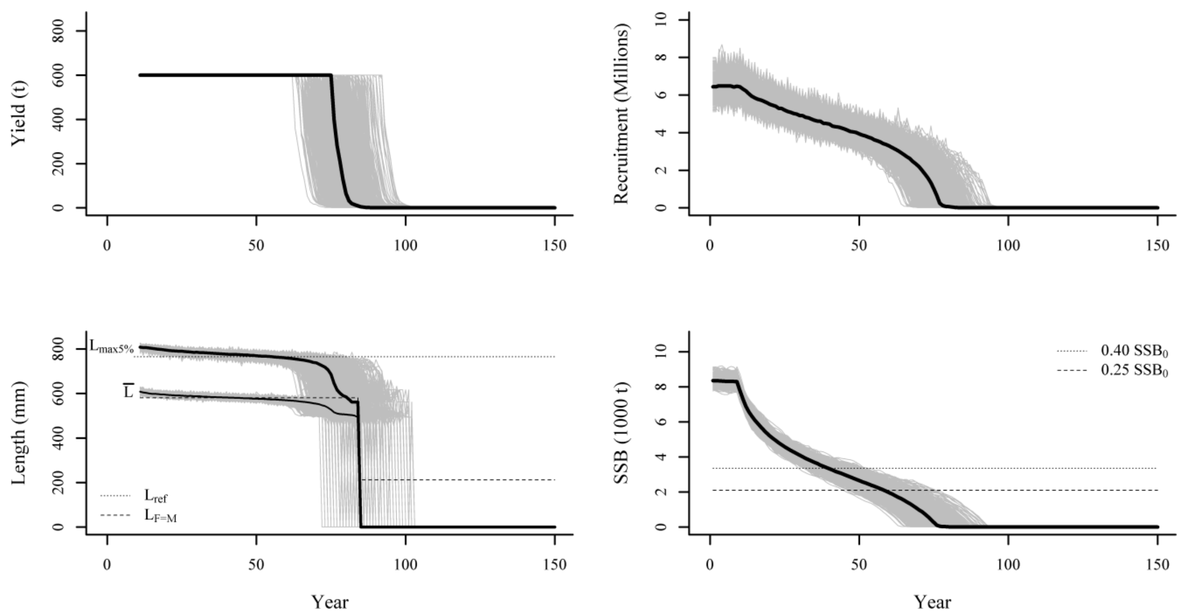

Figure A 5. Constant yield baseline scenario of an overexploited stock of Cuckoo ray. L_c=450, constant TAC of 600 t, 1000 simulations.

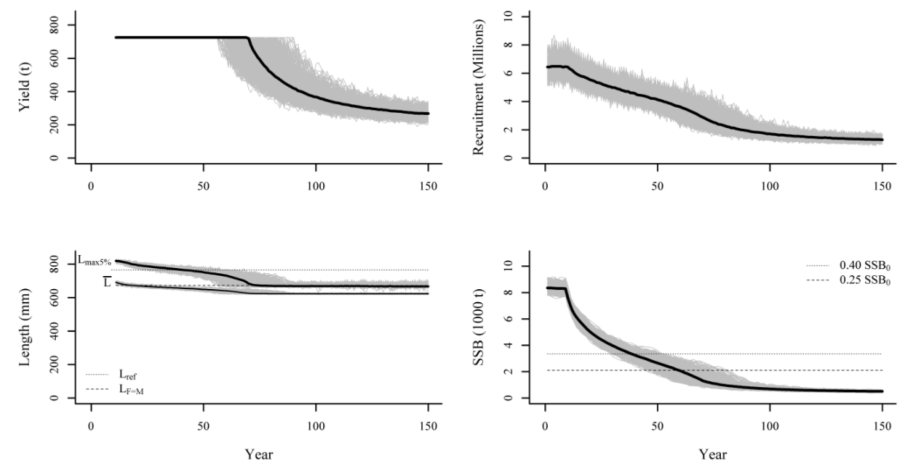

Figure A 6.Constant yield baseline scenario of an overexploited stock of Cuckoo ray. L_c=600, constant TAC of 600 t, 1000 simulations.

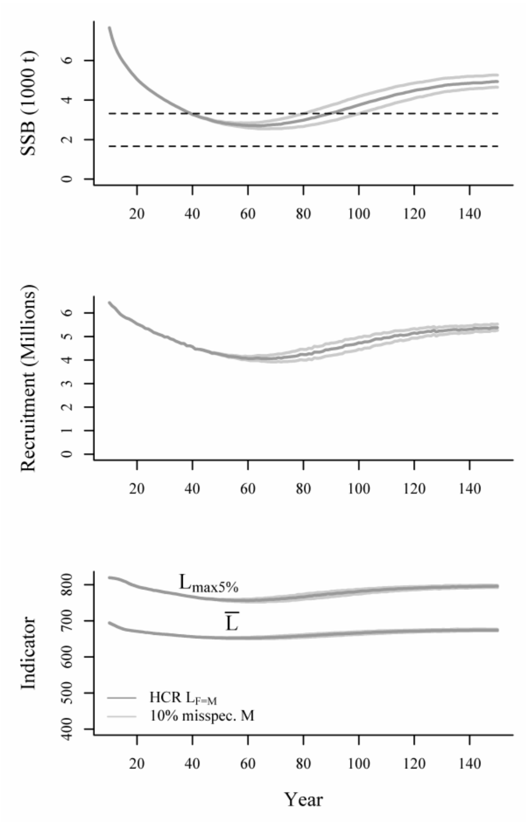

Figure A 7. Misspecification of M (±10%). Median values of results for 1000 simulations for $L_{50\%}$=600. HCR $\bar{L}/L_{F=M}$. For L_c>L_{mat}, parameter misspecification does not lead to stock collapse. Overestimation of M leads to some increase in risk to fall below biomass thresholds during the simulation period.

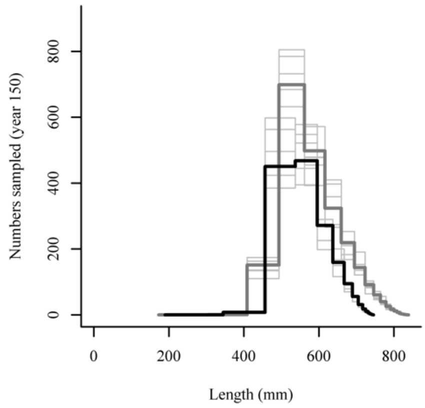

Figure A 8. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, sampling distribution at 1% subsampling (baseline).

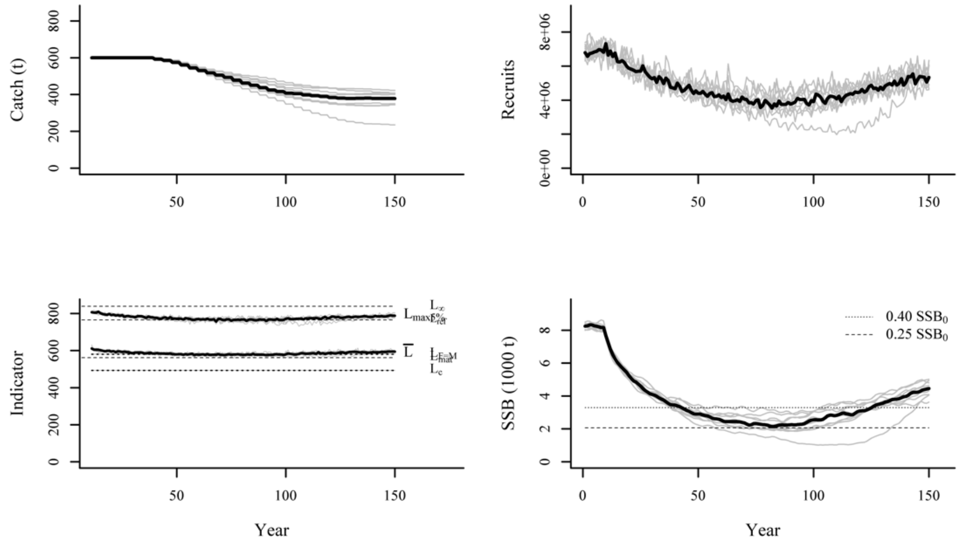

Figure A 9. HCR $\bar{L}/L_{F=M}$, constraint (-15%, 15%), $L_{50\%}$=450, results at 0.2% subsampling, ten simulations. Reduced sampling, indicators vary slightly.

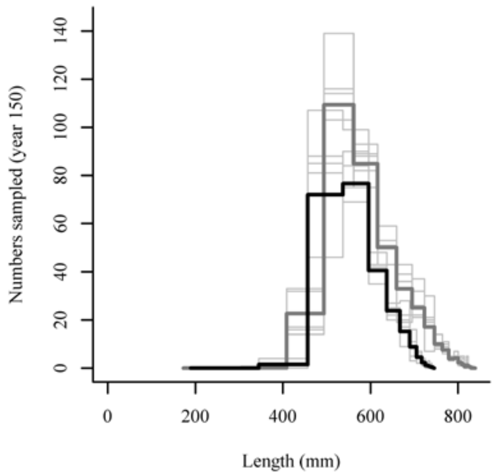

Figure A 10. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, sampling distribution at 0.2% subsampling.

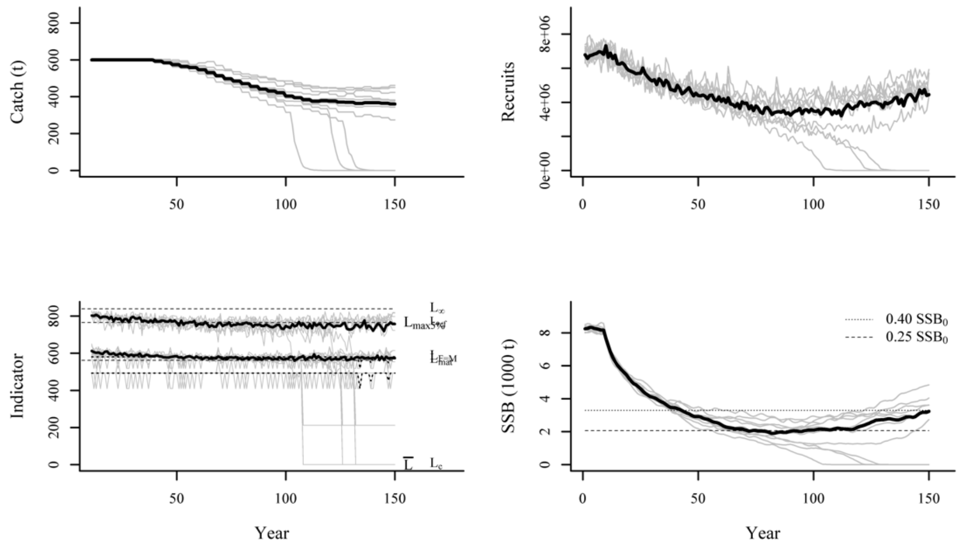

Figure A 11. HCR $\bar{L}/L_{F=M}$, constraint (-15%, 15%), $L_{50\%}$=450, results at 0.02% subsampling. Stocks collapse due to insufficient sampling and high variability of indicator, ten simulations.

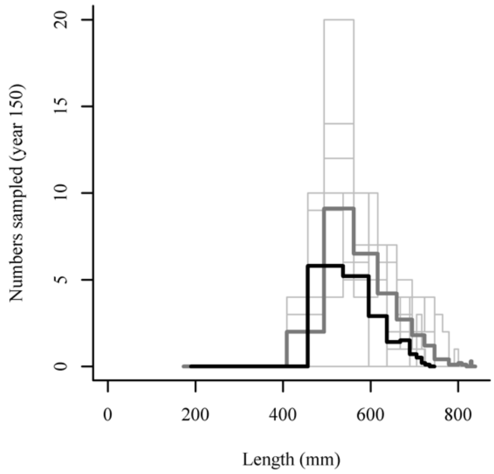

Figure A 12. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, sampling distribution at 0.02% subsampling. Insufficient sampling.

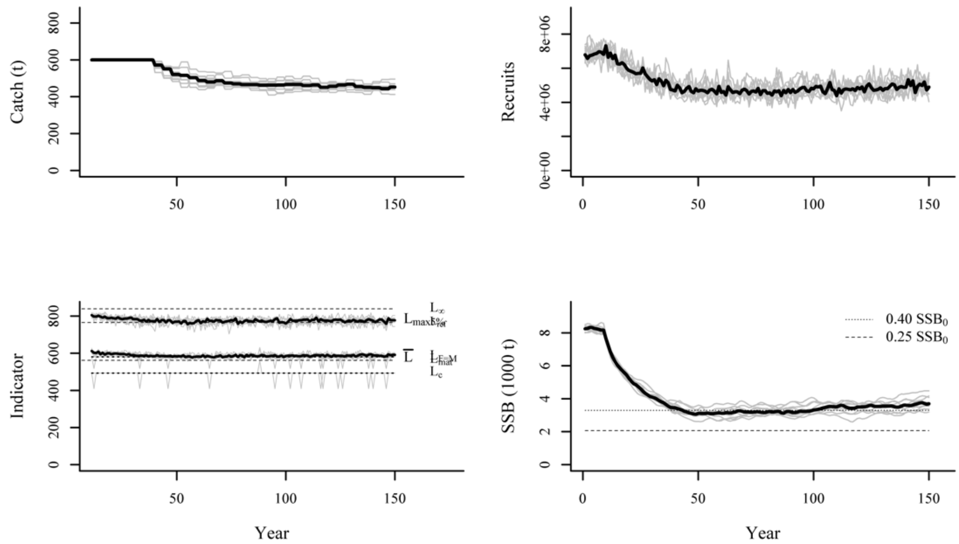

Figure A 13. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, results at 0.04% subsampling, ten simulations. Some variability of indicators, but HCR still performs.

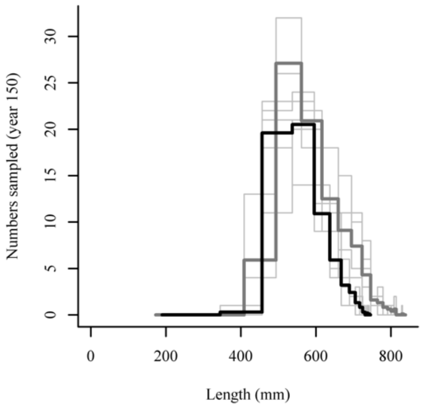

Figure A 14. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, sampling distribution at 0.04% subsampling.

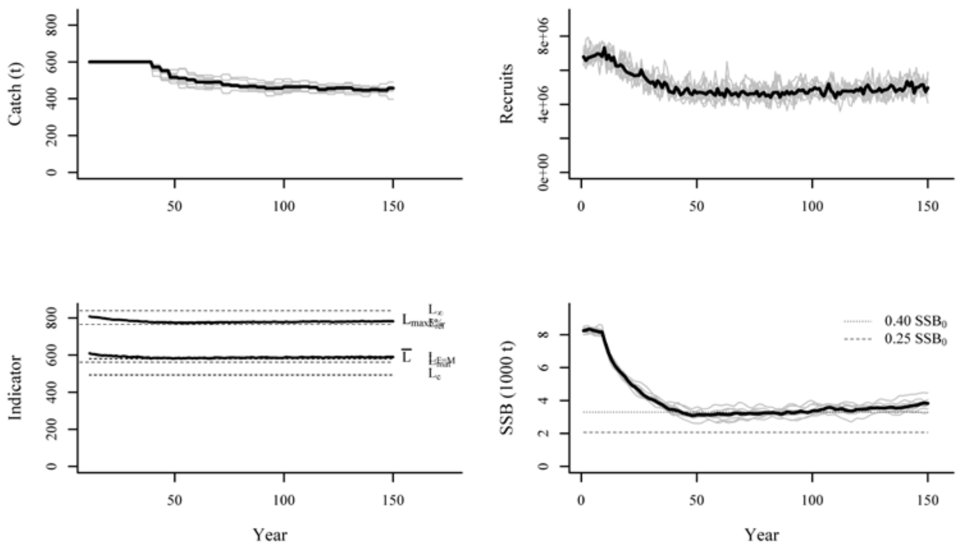

Figure A 15. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, results at 4% subsampling for comparison, ten simulations.

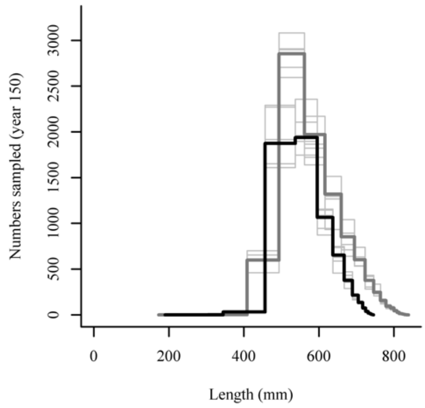

Figure A 16. HCR combined $\bar{L}/L_{F=M}$ and CPUE (2o3), constraint (-25%, 15%), $L_{50\%}$=450, sampling distribution at 4% subsampling for comparison.

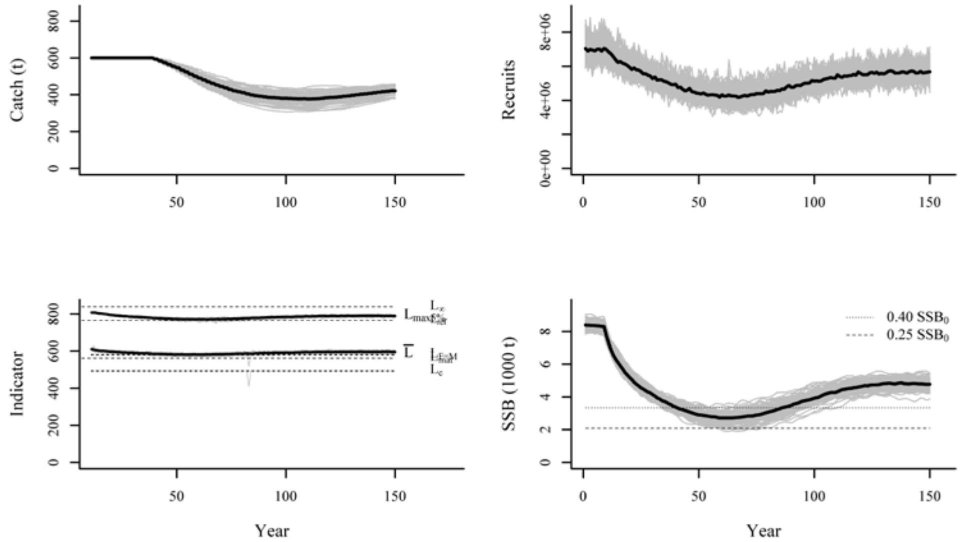

Figure A 17. HCR $\bar{L}/L_{F=M}$, $L_{50\%}$=450, 100 simulations with biennial assessment and TAC adjustment.

References

Andrews, J. M., Gurney, W. S. C., Heath, M. R., Gallego, A., O'Brien, C. M., Darby, C., and Tyldesley, G. 2006. Modelling the spatial demography of Atlantic cod (*Gadus morhua*) on the European continental shelf. Canadian Journal of Fisheries and Aquatic Sciences, 63: 1027–1048.

Gallagher, M. J., Nolan, C. P., and Jeal, F. 2005. Age, Growth and Maturity of the commercial ray species from the Irish Sea. Journal of Northwest Atlantic Fisheries Science, 35: 47–66.

Gurney, W. S. C., Tyldesley, G., Wood, S. N., Bacon, P. J., Heath, M. R., Youngson, A., and Ibbotson, A. 2007. Modelling length-at-age variability under irreversible growth. Canadian Journal of Fisheries and Aquatic Sciences, 64: 638–653.

ICES. 2018a. Report of the Working Group on Elasmobranch Fishes (WGEF), 19–28 June 2018, Lisbon, Portugal. ICES CM 2018/ACOM: 16: 1306 pp.

ICES. 2018b. Report of the Workshop on Length-Based Indicators and Reference Points for Elasmobranchs (WKSHARK4), 6–9 February 2018, Ifremer, Nantes (France). ICES CM/ACOM: 37: 112pp.

ICES. 2012. Report of the Workshop to finalise the ICES data-limited Stocks (DLS) methodologies documentation in an operational form for the 2013 advice season and to make recommendations on target categories for data-limited stocks (WKLIFE II), 20–22 November 2012, Copenhagen, Denmark. ICES CM2012/ACOM:79: 1–46.

Jardim, E., Azevedo, M., and Brites, N. M. 2015. Harvest control rules for data-limited stocks using length-based reference points and survey biomass indices. Fisheries Research, 171: pp 12–19.

Jennings, S., Kaiser, M. J., and Reynolds, J. D. 2001. Marine Fisheries Ecology, Blackwell Publishing.

McCully, S. R., Scott, F., and Ellis, J. R. 2012. Lengths at maturity and conversion factors for skates (Rajidae) around the British Isles, with an analysis of data in the literature. ICES Journal of Marine Science, 69: 1812–1822.

Miethe, T., Reecht, Y., and Dobby, H. In prep. Reference points for length-based indicator Lmax5% to support assessment of size structure and status of data-limited stocks and fisheries.

Probst, W. N., Kloppmann, M., and Kraus, G. 2013. Indicator-based status assessment of commercial fish species in the North Sea according to the EU Marine Strategy Framework Directive (MSFD). ICES Journal of Marine Science, 70: 694–706.

R Core Team. 2017. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Speirs, D. C., Guirey, E. J., Gurney, W. S. C., and Heath, M. R. 2010. A length-structured partial ecosystem model for cod in the North Sea. Fisheries Research, 106: 474–494.

Taylor, I. G., Gertseva, V., Methot, R. D., and Maunder, M. N. 2013. A stock–recruitment relationship based on prerecruit survival, illustrated with application to spiny dogfish shark. Fisheries Research, 142: 15–21.

Then, A. Y., Hoenig, J. M., Hall, N. G., and Hewitt, D. A. 2015. Evaluating the predictive performance of empirical estimators of natural mortality rate using information on over 200 fish species. ICES Journal of Marine Science, 72: 82–92.

Then, A. Y., Hoenig, J. M., Hall, N. G., and Hewitt, D. A. 2018. Corrigendum. ICES Journal of Marine Science, 75: 1509.

Thorson, J. T., and Kristensen, K. 2016. Implementing a generic method for bias correction in statistical models using random effects, with spatial and population dynamics examples. Fisheries Research, 175: 66–74.

Annex 2: Working document–Linking performance of catch rules to life-history traits

Simon H. Fischer, José A. A. De Oliveira, Laurence T. Kell.

Executive Summary

The analysis presented in the WKLIFE VII report was limited by the number of stocks considered (only four representative stocks were considered in the detailed analysis) and showed some promise in linking performance of the catch rules to life-history traits (using the ratio between natural mortality and intrinsic growth rate of the von Bertalanffy growth equation, *M*/*k*). The work presented here extends the analysis to 29 stocks, and explicitly deals with the link between performance of the catch rules and life-history traits. The extension to 29 stocks with a range of life-history parameters increases the opportunity to generalise the conclusions. A penalised regression technique was used to investigate which of the life-history parameters were most influential on six key performance statistics. This analysis found that the von Bertalanffy growth parameter *k* was the most influential. Subsequently, a cluster analysis was performed using the median of the SSB time-series relative to B_{MSY} for the 29 stocks. If only two clusters were considered, these correspond to one cluster with *k* at or above 0.38 (stocks that collapsed) and another with *k* at or below 0.32 (for stocks that survived). The general conclusion with regard to *k* is that catch rule 3.2.1 should not be used for stocks with $k > 0.32$. An analysis of tuning with a multiplier applied to catch rule 3.2.1 indicated a trade-off between improved risk and loss of yield within each cluster, and stocks ended up overshooting B_{MSY} by some margin (even for multipliers below, but still close to 1). If a general multiplier was needed for stocks with $k \leq 0.32$, then a multiplier of no more than 0.8 would ensure the risk of falling below B_{lim} would not exceed 5%. If a multiplier was applied based on more detailed information about *k*, then for stocks with *k* in the range 0.08–0.19, a multiplier of 0.8–0.85 (i.e. no more than 0.85) would be needed, and for stocks with *k* in the range of 0.20–0.32, a multiplier of 0.8–0.9 (i.e. no more than 0.9) would be needed in order to ensure the risk of falling below B_{lim} would not exceed 5% in both cases. These values are conditional on the assumptions of the simulation study. The performance could be improved somewhat with an upper TAC constraint of 1.2 (+20% change) in combination with a lower TAC constraint of 0.7 (-30% change). Using more recent data also improved the performance, i.e. reducing the lag between the index of stock status and setting advice When the catch rule was implemented without uncertainty and reference points were based on MSY, then most stocks (with $k \leq 0.32$) approached B_{MSY}.

Introduction

This Annex presents an extension of the work described in the WKLIFE VII report (ICES, 2018), and links the performance of catch rules to life-history traits. The number of stocks considered was extended to 29 fish and shellfish stocks, for which a simulation or operating model was built, based on life-history parameters (Table 1). The operating model was built using the FLife R package, part of FLR[1].

[1] http://www.flr-project.org/

For consistency reasons and to facilitate comparisons, stock names have been kept the same as for the work presented at WKLIFE VII (ICES, 2018) and therefore do not necessarily represent correct stock names as used by ICES. Although some of the names include area specifications, they should not be considered to be specific to these areas. The areas merely indicate areas from which life-history parameters have been extracted and the analysis presented here does not intend in any way to represent real stock dynamic for specific stocks.

The stocks created were subjected to two distinct fishing histories (one-way trip and roller-caster scenario). Based on this, a full feedback stochastic MSE simulation was conducted. For details on how the stocks were created and on the structure for the MSE simulations, see the WKLIFE VII report (ICES, 2018).

Table 1. The 29 stocks simulated in this study and their life-history parameters used. *a* and *b* are the parameters used for the length–weight conversion, L_{inf}, t_0 and *k* are von Bertalanffy growth parameters, L_{max} is the maximum length, L_{50} and A_{50} are length and age at 50% maturity. Please note that some of the names include area specifications but this does not mean that the stock dynamics simulated for these stocks resembles their real situation.

name	common	short	area	*a*	*b*	L_{max}	L_{inf}	L_{50}	A_{50}	t_0	*k*
Clupea harengus	Herring	her.27.irls	Celtic Seas	0.0048	3.198		33	23			0.606
Pollachius pollachius	Pollack	pol.27.3a4	North Sea	0.0076	3.069		85.6	47.1			0.19
Molva molva	Ling	lin.27.3a4a6–91214	Widely	0.0036	3.108		119	74	7.2		0.14
Sebastes norvegicus	Rose fish	Smn-con	Northern	0.0178	2.972		50.2	40.3		0.08	0.11
Mullus surmuletus	Red mullet	mur.27.67a–ce–k89a	Celtic Seas	0.0057	3.243		47.5	16.9			0.21
Scopthalmus maximus	Turbot	tur.27.4	North Sea	0.0149	3.079		66.7	34.2	2.2	0.29	0.32
Microstomus kitt	Lemon sole	lem.27.3a47d	North Sea	0.0123	2.971		37	27			0.42
Lepidorhombus spp.	Megrim	lez.27.4a6a	North Sea	0.0022	3.3433		54	23	3		0.12
Ammodytes spp.	Sandeels	san.sa.4	North Sea	0.0049	2.783		24	12			1
Pleuronectes platessa	Plaice	ple.27.7fg	Celtic Seas	0.011	2.958		48	22.9			0.23
Merlangius merlangus	Whiting	whg.27.7b–ce–k	Celtic Seas	0.0103	2.395		38	28		-1.01	0.38
Melanogrammus aeglefinus	Haddock	had.27.7a	Celtic Seas	0.0113	2.96		79.9		2	-0.36	0.2
Lophius piscatorius	White anglerfish	mon.27.7abd	Celtic Seas	0.0198	2.895	133.1	105.555	73		-0.38	0.18
Lophius piscatorius	Anglerfish	anf.27.3a46	North Sea	0.0297	2.841		106	61			0.18
Nephrops norvegicus	Norway lobster	nep.fu.2829	Biscay-Iberia	0.00028	3.229		70	28.4			0.2
Scyliorhinus canicula	Lesser spotted dogfish	syc.27.67a–ce–j	Celtic Seas	0.0019	3.1541	70	75.14	57	7.9	-0.96	0.15
Scyliorhinus canicula	Lesser spotted dogfish	syc.27.8c9a	Biscay-Iberia	0.0022	3.119	68	66.2	59.1		-0.71	0.23
Mustelus spp	Smooth-hound	sdv.27.nea	Widely	0.001	3.27	124	123.5	81.9			0.15
Raja clavata	Thornback ray	rjc.27.7afg	Celtic Seas	0.0024	3.2653	104	139.5	71.8	6.13	-1.84	0.09
Raja clavata	Thornback ray	rjc.27.3a47d	North Sea	0.0045	3.0686	94	118	77.1		-0.88	0.14

name	common	short	area	*a*	*b*	L_{max}	L_{inf}	L_{50}	A_{50}	t_0	*k*
Sardina pilchardus	Pilchard	pil.27.78abd	Celtic Seas	0.0053	3.162	27.6	22	14.3			0.6
Zeus faber	John Dory	jnd	Celtic Seas	0.0399	2.754		50.8	34.5		-1.47	0.47
Chelidonichtys lucerna	Tub gurnard	gut	Celtic Seas	0.0043	3.21		66.8	40.1		-0.46	0.32
Pagellus bogaraveo	Blackspot seabream	sbr.27.6–8	Celtic Seas	0.0148	3.004		41.25	22		-1.16	0.22
Anarchias lupus	Wolffish	wlf	North Sea	0.0046	3.185		115.1	21.5	3.8	-0.39	0.11
Scophthalmus rhombus	Brill	bll.27.3a47de	North Sea	0.014	3.01		58	31.3	1.6	-0.27	0.38
Argentina silus	Greater argentine	aru.27.6b7–1012	Widely	0.005	3.075		44	38	8.2		0.23
Engraulis encrasicolus	Anchovy	ane.27.9a	Biscay-Iberia	0.005	3.107	23		16.8			0.44
Lophius budegassa	Black-bellied anglerfish	ank.27.78abd	Celtic Seas	0.0259	2.858		110.1	54.8	9	0.39	0.08

Methods

Catch rule

The main focus of this study was catch rule 3.2.1 from WKMSYCat34 (ICES, 2017):

$$C_{y+1} = C_{\text{current}} r f b$$

C_{y+1} is the advised catch for the next year, and $C_{current}$ was taken as C_{y-1}. The options selected for the components of the catch rule are the ones which performed best at WKLIFE VII. Component r was set as the "2 over 3" rule, i.e. calculated as the average of the last two index values divided by the average of the three preceding years. Component f was defined as $f = L_{current}/L_{F=M}$ where $L_{current}$ is the current mean length in the catch above the length of first capture and $L_{F=M}$ is a reference point derived from the Beverton–Holt equilibrium formula assuming $F = M$ and using $M/K = 1.5$. Component b is a biomass safeguard defined as $b = \min\left\{1, \frac{I_{current}}{I_{trigger}}\right\}$ where $I_{current}$ is the current index level and $I_{trigger}$ set as 1.4 times the lowest observed value.

The catch rule was implemented for a total simulation period of 100 years and the catch was set biennially.

Performance of catch rule

The performance of the catch rule was assessed based on six performance statistics:

- Yield (the catch achieved over the future simulated period, expressed as a proportion of the catch when fishing at F_{MSY});
- Risk of stock collapse (proportion of the simulation period where the stocks is below 0.1% of virgin biomass);
- Risk of the stock falling below B_{lim} (B_{lim} is defined as the stock level where recruitment is at 70% of recruitment achieved at virgin biomass, i.e. 16.3% of virgin SSB for all stocks, because they have the same value of steepness (h) for the Beverton–Holt stock–recruitment relationship);
- Interannual variation in catch (average over simulation period for TAC years, i.e. in case of biennial TAC, every second year is used only);
- Stock status (two performance statistics: SSB and F relative to MSY reference points, averaged over simulation period).

Initial analysis revealed that for some stocks and scenarios, the stocks collapsed and catches were reduced to zero as a result. Depending on stock productivity, some stocks subsequently recovered towards virgin biomass due to the zero catch. This behaviour was deemed inappropriate to further exploration of the performance as it implied a reduced risk. Consequently, running the simulations, once an iteration of a scenario had collapsed, the stock level and catch in subsequent simulation years were both set to zero.

Penalised regression

The stocks were simulated based on a set of life-history parameters. In order to determine which of the stock characteristics influenced the performance of the catch rule, a penalized regression model was applied (glmnet; Friedman *et al.*, 2010). Penalization was applied to the analysis because many of the predictor variables are highly correlated, rendering ordinary linear models of limited value. Glmnet was used as this provides procedures for fitting the entire elastic-net regularization path from the lasso to the ridge regression (Zou and Hastie, 2005; Tibshirani, 1996; Hoerl and Kennard, 1988). The lasso regression selects only the most important parameters, whereas a ridge regression retains all predictor variables. The following parameters were used as predictor variables: a, b (length–weight relationship), L_{inf}, k, t_0 (von Bertalanffy growth parameters), a_{50} (age at 50% maturity), α,β (Beverton–Holt stock–recruitment parameters), $spr0$ (spawning potential ratio), L_{opt} (mean length when the stock is at MSY level), r, r_c (growth rate and conditional growth rate at MSY), M (natural mortality), M/k, F_{MSY}/M (F_{MSY} relative to M) and B_{MSY}/B_0 (B_{MSY} relative to virgin biomass, i.e. location of peak in production curve).

A multi-Gaussian model was applied that selected the predictor variable(s) that could explain all of the six performance statistics (yield, collapse risk, B_{lim} risk, interannual variation, stock status in terms of F and SSB).

Clustering

In order to identify groups of similar performing stocks from within the range of life histories tested, a time-series clustering approach was adopted. The Dynamic Time Warping technique (DTW; Berndt and Clifford, 1994; Aghabozorgi *et al*., 2015) was selected as a distance measure. DTW is an elastic method that allows clustering of time-series with similar patterns, even when the temporal dimension between the time-series differs, and has been applied across a wide range of applications. The relative stock status (SSB in relation to B_{MSY}) was selected as a time-series index because it provided the overall best indicator of the performance of the catch rule over time. Biomass was used in relative terms because the catch rule's long-term target is MSY, and consequently both undershooting of B_{MSY} (overfishing) and overshooting (loosing yield through fishing below MSY) are evident and comparable for all simulated stocks. Several clustering algorithms (partitional, fuzzy, hierarchical) were trialled. Partitional and fuzzy clustering imply stochasticity because the results depend on the random location of where the algorithm starts. This proved unreliable for the cluster analysis presented here, because the results were unstable, and even iterating the analysis many (thousands) times did not lead to stable and reproducible clusters. Hierarchical clustering on the other hand does not rely on stochasticity for the formation of the clusters. Additionally, once a hierarchical cluster analysis is conducted, the output can be visualised in a dendrogram and any arbitrary number of clusters can be pursued without having to rely on potentially biased cluster validity indices to select the optimum number of clusters.

Tuning of the catch rule

Various modifications of the catch rule were explored. One option tested was the addition of a multiplier x to the catch rule: $C_{y+1} = C_{\text{current}}\, r\, f\, b\, x$. Multipliers of 0.5, 0.6, 0.7, 0.8, 0.85, 0.9, and 0.95 were evaluated for all stocks and fishing histories.

By default, catch rule 3.2.1 does not include any constraints on the catch advice. In order to examine the impact of constraints on the performance of the catch rule interannual limits on the relative variation in catches were evaluated. The constraints were defined as the maximum change in the advised catch compared to the last catch. Eight lower limits (0, i.e. no constraint, 0.5, 0.6, 0.7, 0.75, 0.8, 0.85 and 0.9), seven upper limits

(1.1, 1.15, 1.2, 1.25, 1.3, 1.5 and no limit) and all combinations of these (56 combinations in total) were implemented for the 29 stocks and two fishing histories.

Data timing

By default, the MSE simulations presented here followed the ICES assessment cycle for category 3 stocks. This meant that the catch rule was applied in an intermediate (assessment) year y based on data up to the previous year (y-1) and the advice was given biennially for the following two years $y+1$ and $y+2$. The data used in the catch rule were from the years up to the year before the intermediate year ($y-1$), that is $y-1$ for the catch data for components C_{y-1} and f, $y-1$ for the index for b, and years $y-5 \dots y-1$ for r. In order to explore the effect of data timing more recent data were included. For the catch, this included data up to the intermediate year y. The survey index was calculated, based on the stock at the beginning of a given year and could therefore be extended two years up to the advice year $y+1$. Additionally, giving advice annually vs. biennially was explored.

Contribution of the components of the catch rule to the advice

Catch rule 3.2.1 comprises four components (C_{y-1}, r, f and b) which are multiplied to obtain the catch advice. The product of the components r, f and b scales the recent catch up or down, depending on the information obtained from the catch and survey, i.e. the deviation of the components from 1 determines their influence. Because the catch rule is a product of several factors, it is difficult to estimate the relative contribution of the individual components. A simpler approach used here was to use the natural logarithm of the components and the sum of the logarithms of the components in a given simulation year then provided a measure of how the advice was changed. On this scale, positive values indicate an increase in the advice whereas negative values indicate a reduction.

Alternative natural mortality in operating model

The operating models for the simulated stocks were created by assuming a length-dependent Gislason natural mortality (Gislason, 2010):

$$\ln(M) = 0.55 - 1.61\ln(L) + 1.44 * \ln(L_{inf}) + \ln(k),$$

where M is natural mortality, L is the length-at-age and L_{inf} and k are von Bertalanffy growth parameters. In order to examine the impact of different natural mortality assumptions, a weight-dependent Lorenzen mortality function $M_W = M_u W^b$ was applied (Lorenzen, 1996), adapted to include a length–weight relationship and the von Bertalanffy growth equation:

$$M = \gamma\{L_{inf}[1 - e^{-k(t-t_0)}]\}^{\delta},$$

where L_{inf}, k and t_0 are von Bertalanffy growth parameters. Parameters $\gamma$and δwere estimated to ensure that the Lorenzen curve went through the points $\{t = 1, M = M_1\}$ and $\{t = 20, M = M_2\}$ for each stock. For M_2 values of 0.1, 0.2 and 0.3 were trialled and M_1 was set to $2M_2$ and $4M_2$. These seven natural mortality combinations (one Gislason mortality, six combinations for Lorenzen mortality) were then tested with two levels of recruitment variability (cv of 0.3 and 0.6), without autocorrelation. The default catch rule 3.2.1, as defined above, was then tested with these options without any other uncertainty (i.e. perfect information, reference length defined as length at F_{MSY}). Due to time constraints, the runs were limited to 50 iterations and a projection period of 50 years. Additionally, modifications to the maximum age were implemented in order to account for increased longevity with lower natural mortality. For the scenarios conducted so far, the maximum age (t_{max}) was defined as the age (rounded up) where the length was at 95% of L_{inf} in the von Bertalanffy growth equation:

$$L_t = L_{inf}(1 - e^{-k(t-t_0)}),$$

solved for t:

$$t = t_0 - \frac{\ln\left(1 - \frac{L_t}{L_{inf}}\right)}{k}$$

and set $L_t = 0.95L_{inf}$ for$t = t_{max}$:

$$t_{max} = t_0 - \frac{\ln\left(1 - \frac{0.95L_{inf}}{L_{inf}}\right)}{k} = t_0 - \frac{\ln 0.05}{k}$$

A second maximum age was defined by using the approximation of Hordyk *et al.* (2014) which defines the age in terms of survival of an unfished population:

$$t_{max} = \frac{\ln P}{M}$$

For the simulations presented here, a survival of $P = 0.05$ was assumed and the final maximum age was chosen as the maximum of the two options presented above.

Perfect information and knowledge scenario

To check whether the catch rule worked when all the information available to the catch rule was available without error, an additional scenario was run for all the simulated stocks and fishing histories. For these scenarios the (default) Gislason natural mortality was applied, and the only uncertainty implemented was the recruitment uncertainty with a cv of 0.3 and without autocorrelation.

The survey index was replaced with the SSB from the operating model to remove the impact of survey selectivity. In the default settings for the simulations presented in this study, the index reference point ($I_{trigger}$) below which the catch is reduced was set to 1.4 times the lowest ever observed value (I_{loss}). For the perfect knowledge scenario, this reference value was set to exactly $B_{trigger}$and in agreement with ICES data-limited guidelines, $B_{trigger}$ was set to $0.5B_{MSY}$. This modification meant that the biomass threshold was set irrespective of the historical exploitation and comparable for all stocks.

The reference length for the f component of the catch rule was defined as the length obtained in the operating model when fishing at F_{MSY}.

Alternative catch rule: catch rule 3.2.2

The alternative catch rule evaluated was WKMSYCat34 catch rule 3.2.2, also known as "Icelandic catch rule" or "F_{proxy} rule" (ICES, 2017). The analysis presented here is an extension of the work presented at WKLIFEVII (ICES, 2018) and uses the same assumptions and uncertainty. This catch rule has the form:

$$C_{y+1} = I_{current} F_{proxy,MSY} \min\left\{1, \frac{I_{current}}{I_{trigger}}\right\},$$

where $I_{current}$ is the biomass index at year $y-1$, $F_{proxy,MSY}$ a proxy harvest rate, and the last component a biomass safeguard with $I_{trigger}$ being a trigger value below which the catch is reduced. To be consistent with catch rule 3.2.1, $I_{trigger}$ was set to I_{loss}×1.4. For $F_{proxy,MSY}$, two harvest rates (measured as the catch divided by the biomass index) were tested, one corresponding to the harvest when the stock was exactly at F_{MSY} for 100 years, and the other based on the catch length reference point $L_{F=M}$. For the latter scenario, the reference length was calculated assuming $M/K = 1.5$, and the stocks were fished at varying fishing mortalities, 100 years for each fishing mortality; the fishing mortality selected was the one which produced a mean length in the catch equal to $L_{F=M}$ and the harvest rate was taken from the end of this 100-year projection. In addition to the default runs with the proxies, the impact of including more recent data was explored.

Results

Figure 42 shows the correlation matrix for the life-history parameters describing the 29 simulated stocks. Many of the parameters are highly correlated, e.g. particularly high positive correlations are evident for the natural mortality (M), von Bertalanffy growth parameter k, F_{MSY}, MSY yield, growth rate r and conditional growth rate r_c.

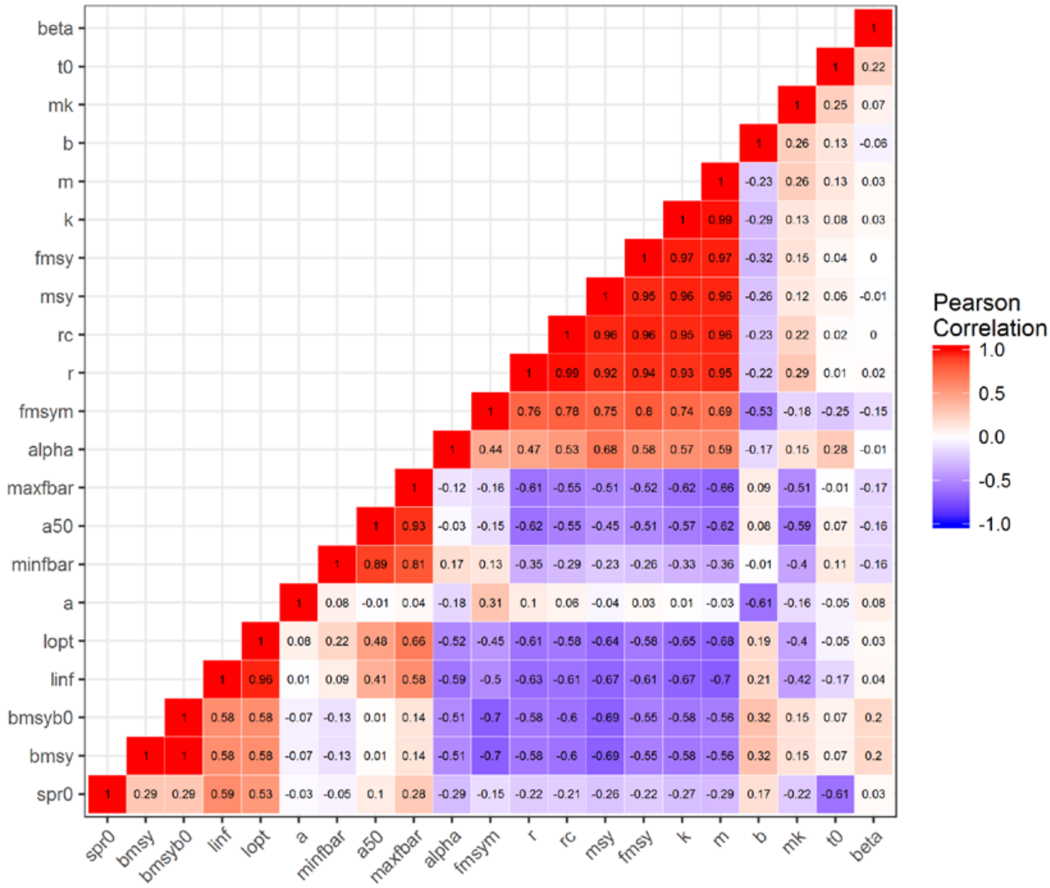

Figure 42. Correlation matrix of life-history parameters describing the simulated stocks.

Penalized regression

Performing the lasso regression resulted in a model fit that selected only the von Bertalanffy growth parameter k to explain the six performance statistics for the one-way fishing scenario. Figure 43 shows the performance statistics as a function of k including the lasso model fit (red lines), applied to all six performance statistics simultaneously, and a linear regression (black lines), applied to each performance statistic separately, for comparison. The model values are displayed in Table 2.

Allowing elastic-net regularization in the penalized regression model led to minor improvements in the model fit (the mean squared error was reduced from 0.5557 to 0.5395, Figure 3), but came at the cost of adding complexity to the model by returning non-zero coefficients for growth rate (r), conditional growth rate (r_c) and natural mortality (M) in addition to k. Consequently, k was selected as the single most important factor for the performance of the catch rule for the simulated stocks. This was particularly evident for the risk and yield. Higher ks were linked to higher risks (for stock collapse and of falling below B_{lim}) and lower long-term yield. Stocks with very low collapse risks were clustered at k values at or below 0.32 whereas risk above 20% were only observed for stocks with k values at or above 0.38. The effect is less pronounced for the stock status and the interannual variation of catches.

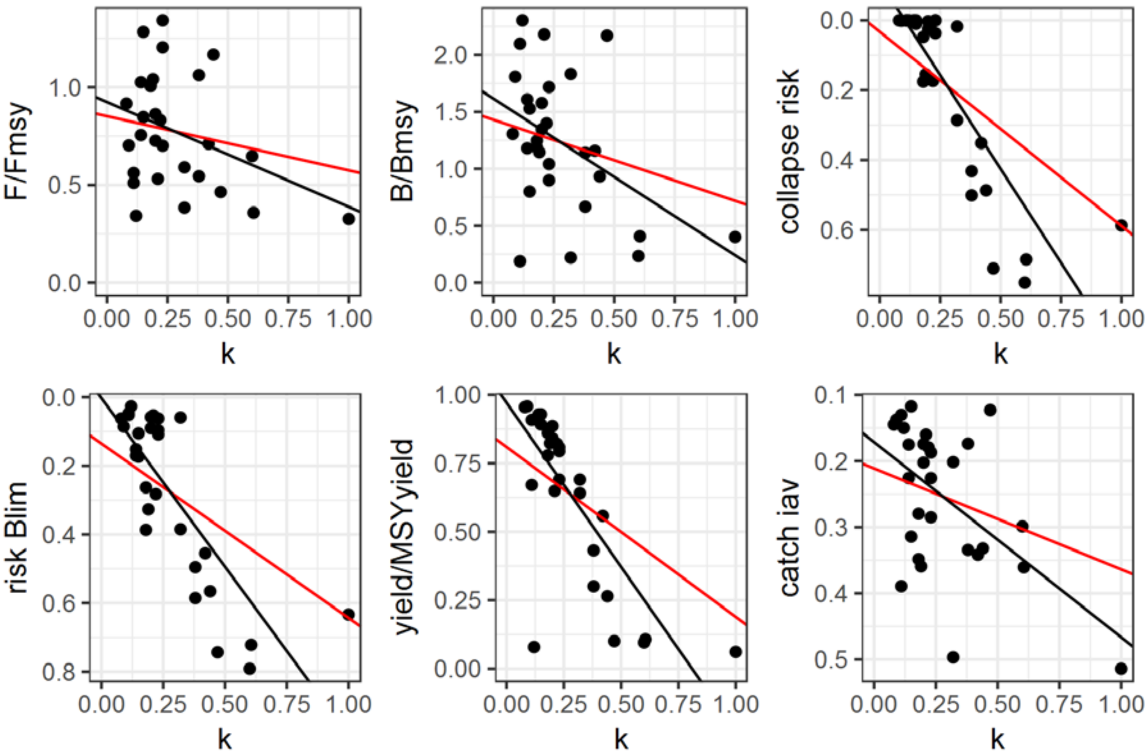

Figure 43. Six performance statistics vs. the von Bertalanffy growth parameter *k* for the catch rule 3.2.1 and the one-way fishing history for all 29 stocks. The red lines show the fit from the lasso regression model, and the black lines a simple linear regression of the data. Please note the inverted axes for the risks and the interannual variation in catch.

Table 2. Coefficients of the lasso model fit to the six performance statistics and the results of linear models fitted individually.

	LASSO REGRESSION			INDIVIDUAL LINEAR MODELS				
	Intercept	k	Combined mse	Intercept	k	R2	p	Combined mse
F/F_{MSY}	0.8520	-0.2774	0.5557	0.9243	-0.5362	0.1349	0.04999	0.5401
B/B_{MSY}	1.4308	-0.7118		1.616	-1.376	0.2070	0.01315	
Collapse risk	0.0328	0.5561		-0.1121	1.075	0.7086	1.052e-08	
Risk B_{lim}	0.1353	0.5081		0.0030	0.9822	0.6383	2.042e-07	
Yield / MSY yield	0.8095	-0.6205		0.9711	-1.200	0.5968	0.5818	
Catch iav	0.2113	0.1526		0.1715	0.2950	0.2902	0.002572	

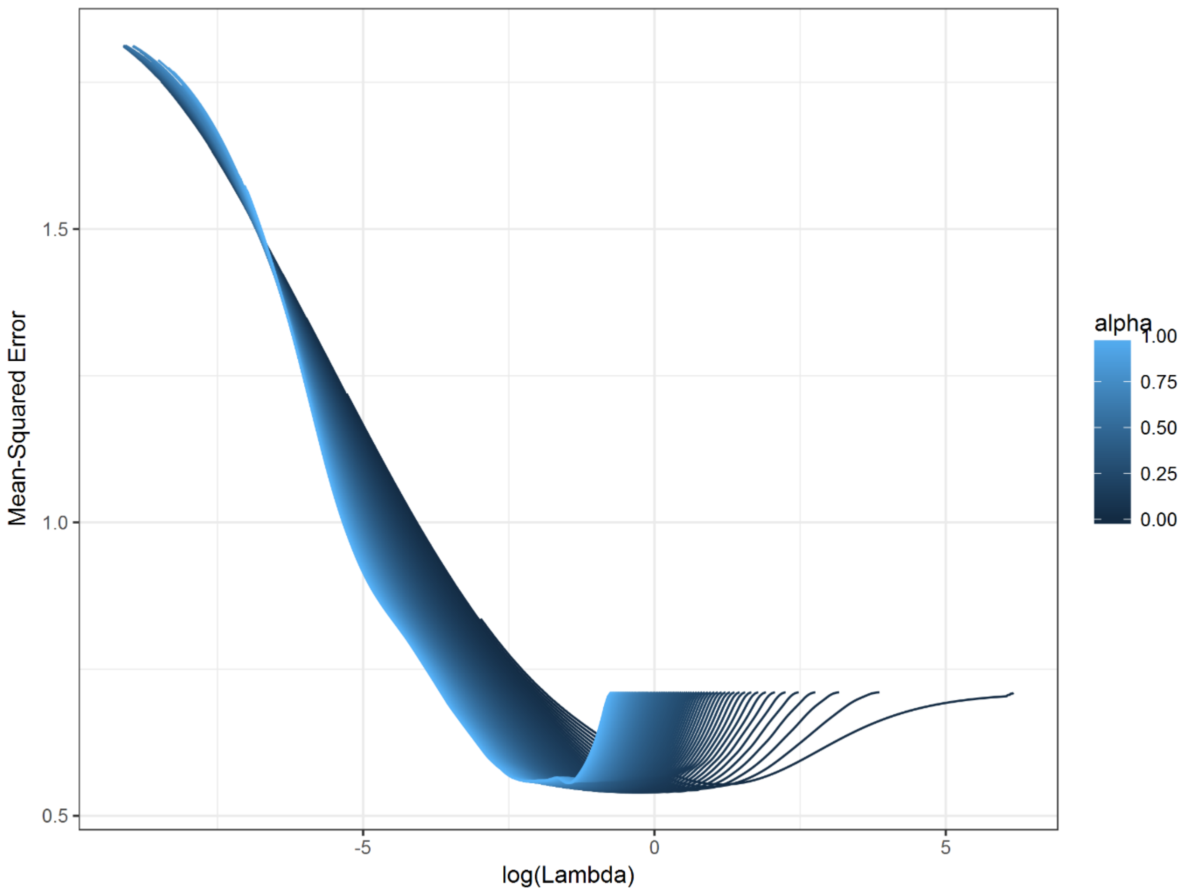

Figure 44. Results on the model fit (expressed as mean-squared error) when elastic-net regularization is allowed in glmnet. Alpha is the elasticnet mixing parameter and alpha = 1 corresponds to the lasso regression and alpha = 0 to the ridge regression. Lambda is the regularization parameter and each lambda value corresponds to a model fit.

Clustering

Clustering was performed on the median of the SSB time-series relative to B_{MSY} for the 29 simulated stocks. Figure 4 shows the results from the hierarchical clustering for up to four clusters. Hierarchical clustering does not compute centroids for the clusters. For plotting purposes (B in Figure 4), centroids for the clusters were calculated *post hoc* as the annual average of the SSB values of all stocks within the cluster. If all stocks were kept in a single cluster, the centroid SSB trend showed a recovery after the start of the MSE simulation and equilibrated at a level slightly above B_{MSY}. The first separation in the hierarchical cluster distinguishes between two distinct patterns (second row in Figure 4B); the first cluster is composed of stocks that experienced early peaks in SSB but collapsed by the end of the simulation period, whereas the stocks in the second cluster survived. This split corresponds well to the von Bertalanffy *k* values for these stocks (Figure 4C). The first cluster (collapsed) is comprised of stocks with *k* at or above 0.38. On the other hand, the stocks with lower *k* (0.32 and below) survived.

Following the dendrogram further, the next two splits occurred within the cluster of surviving stocks. First, there is a separation of stocks that stay around $\mathrm{B}_{\mathrm{MSY}}$ in the long term and the ones that end up markedly above B_{MSY} (third row of Figure 4B). These stocks are mainly characterised by *k* values around the median of the simulated range, although two of the stocks inside this cluster have *k* values at the lower end of the total range (megrim and redfish). For megrim, the catch was reduced drastically at the beginning of the simulation and approaches zero, consequently, the stock moves towards virgin biomass. Redfish displayed a similar behaviour; however, the catch recovers later in the simulation and the stock declines again from very high levels.

Second, the stocks reaching levels above B_{MSY} are divided further into one cluster where the SSB converged at around $2B_{MSY}$ and one cluster where the SSB approaches levels close to $3B_{MSY}$ (fourth row of Figure 4B). In terms of *k*, these stocks overlap and no clear distinction is evident. Moving further along the dendrogram, these clusters are divided further; however, clusters increasingly represent individual stocks instead of general trends, because stocks are singled out as the number clusters grows.

The clusters in Figure 4 are colour coded and this colour code is maintained throughout this Appendix. Results in this figure are for the one-way trip scenario, but results for the roller-coaster scenario are almost identical when considering four clusters.

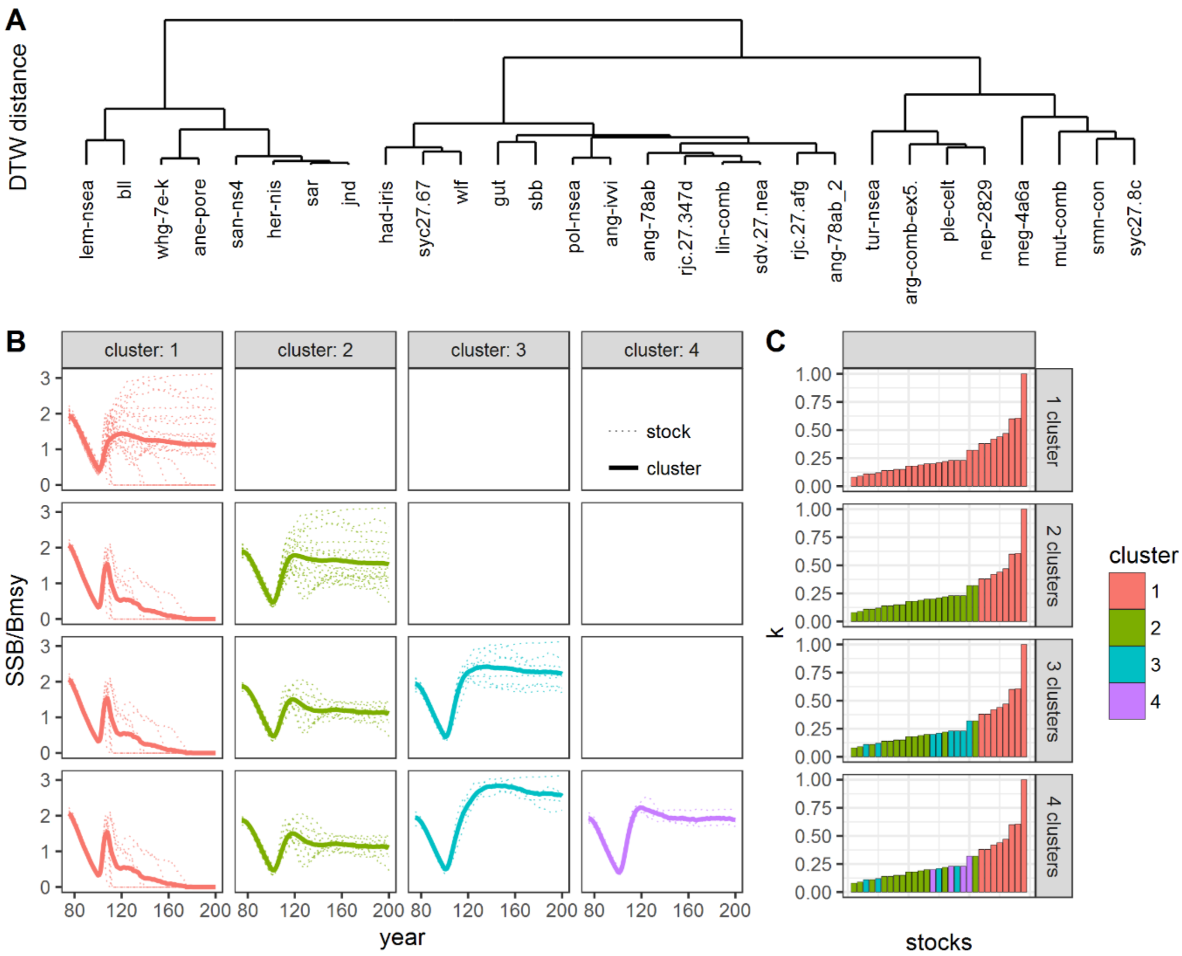

Figure 45. Results of the hierarchical clustering approach of relative SSB time-series from the simulations of catch rule 3.2.1 and the one-way fishing history. A shows a dendrogram of the time-series for the 29 simulated stocks. The y-axis corresponds to the dynamic time warping (DTW) distance between the time-series. B represents the median SSB time-series for all stocks (dotted lines) and the centroids (solid bold line). Rows represent the number of clusters and each column is one cluster. C shows von Bertalanffy *k* values for all stocks, sorted in ascending order and colour-coded for the clusters shown in B.

Multiplier

Adding a multiplier of less than one to the catch rule reduced the risk (both risk of collapse and risk of falling below B_{lim}) for all stocks and in both fishing scenarios (Figure 5). This risk reduction was a result of higher terminal SSB values, and the smaller the multiplier, the higher the SSB values, capped at the top at the virgin biomass level. For the stocks where the median SSB collapsed during the simulation period (cluster 1 in Figure 4, coloured red in Figure 5), adding the multiplier delayed this collapse, and reducing the multiplier further, the collapse was avoided altogether. This behaviour of the SSB trajectory was stock specific. For example, in the default catch rule, the median SSB of anchovy (ane-pore) in the one-way fishing scenario reached zero roughly 40 years after the start of the simulation, and adding a multiplier of only 0.95 avoided this collapse. On the other hand, pilchard (sar) and John Dory (jnd) collapsed in the roller-coaster fishing scenario within approximately five years, and this collapse could only be averted by implementing a multiplier of 0.8 or below. The performance of the catch rule for these cluster 1 stocks was highly sensitive to small changes of the multiplier. Once a threshold multiplier was reached, the long-term stock levels increased heavily and overshot B_{MSY}, thereby losing out on yield.

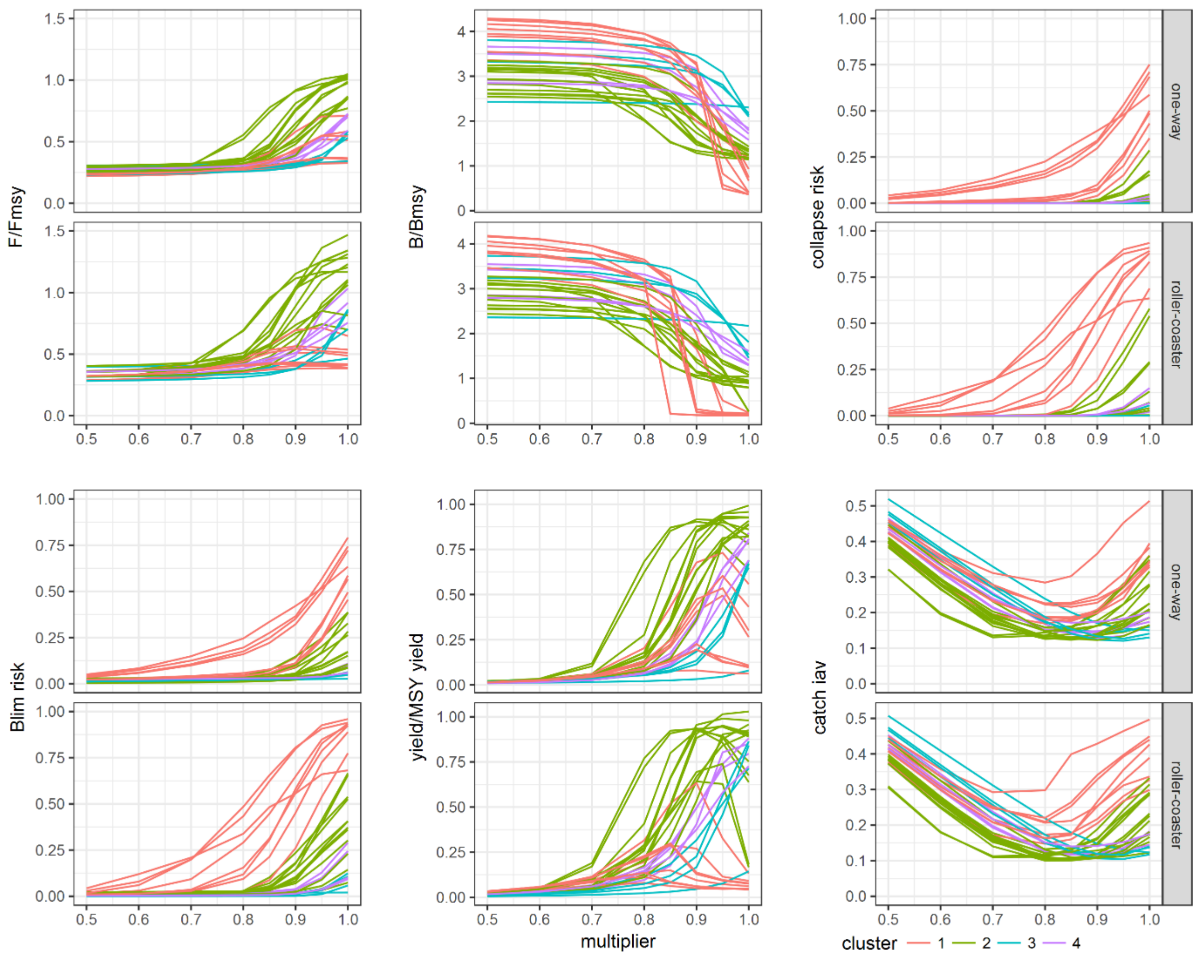

Figure 46. Effect of implementing a multiplier on the performance of catch rule 3.2.1. The clusters correspond to the ones defined in Figure 4.

Stocks in cluster 2 were kept around B_{MSY} in the long term, when the catch rule was applied without a multiplier. Introducing the multiplier for these stocks reduced their risks (green stocks in Figure 5) but moved them above B_{MSY}. Stock levels for stocks from clusters 3 and 4, where shifted further above B_{MSY} when the multiplier was added.

For 16 out of the 29 tested stocks, adding the multiplier reduced the yield. For the remaining 13 stocks, the maximum was achieved within a range 0.9–0.95. When considering all stocks together, there does not seem to be a multiplier that increases risk performance for all stocks without jeopardizing yield for some.

The stocks in clusters 2–4 overlap in terms of k values (Figure 45) but most stocks in cluster 2 (which end up around B_{MSY}) have k values below 0.20 whereas most stocks in cluster 3 and 4 have k values at or above 0.20. Figure 47 shows the risks for the stocks when they are separated into two groups (low: $0.08 \leq k \leq 0.19$ and medium: $0.20 \leq k \leq 0.32$). The median of risk of dropping below B_{lim} crosses the 5% risk threshold at a multiplier level between 0.9 and 0.95 for the low k stocks and between 0.95 and 1 for the medium k stocks. This means that the highest multiplier where the median risk is below 5% is 0.9 for the low k stocks and 0.95 for the medium k stocks. However, it should be noted that the risks presented here depend crucially on the assumption of the operating model, the set-up of the MSE simulation, the implementation of uncertainty, and the setting of what is deemed an acceptable risk threshold. Although 5% is use as the B_{lim} risk threshold (consistent with what ICES uses), this level could be considered arbitrary because it depends on the assumptions underlying the MSE.

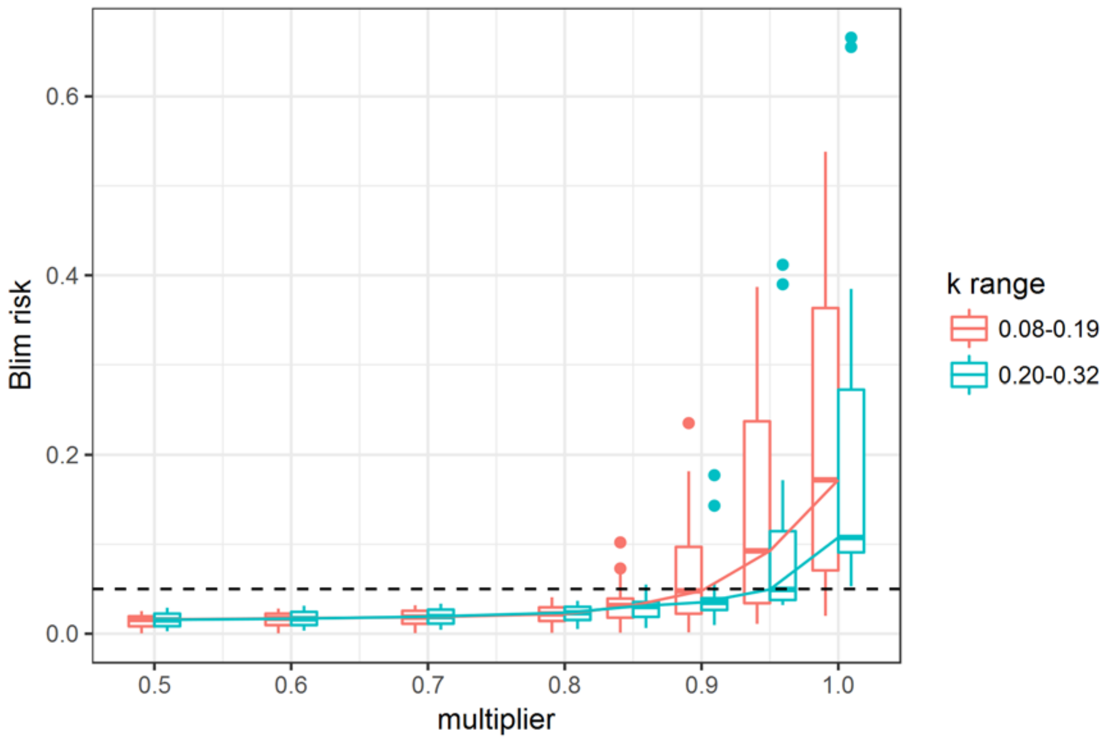

Figure 47. B_{lim} risk for the stocks in clusters 2–4, split into two groups depending on k. The boxplots show the range of risk for the stocks combined for the two fishing histories for a given multiplier and the solid line the median. The black dashed line indicates the 5% probability.

Catch constraints

Implementing an upper catch constraint reduced the risks for all stocks and more restrictive constraints led to lower risks (Figure 48).

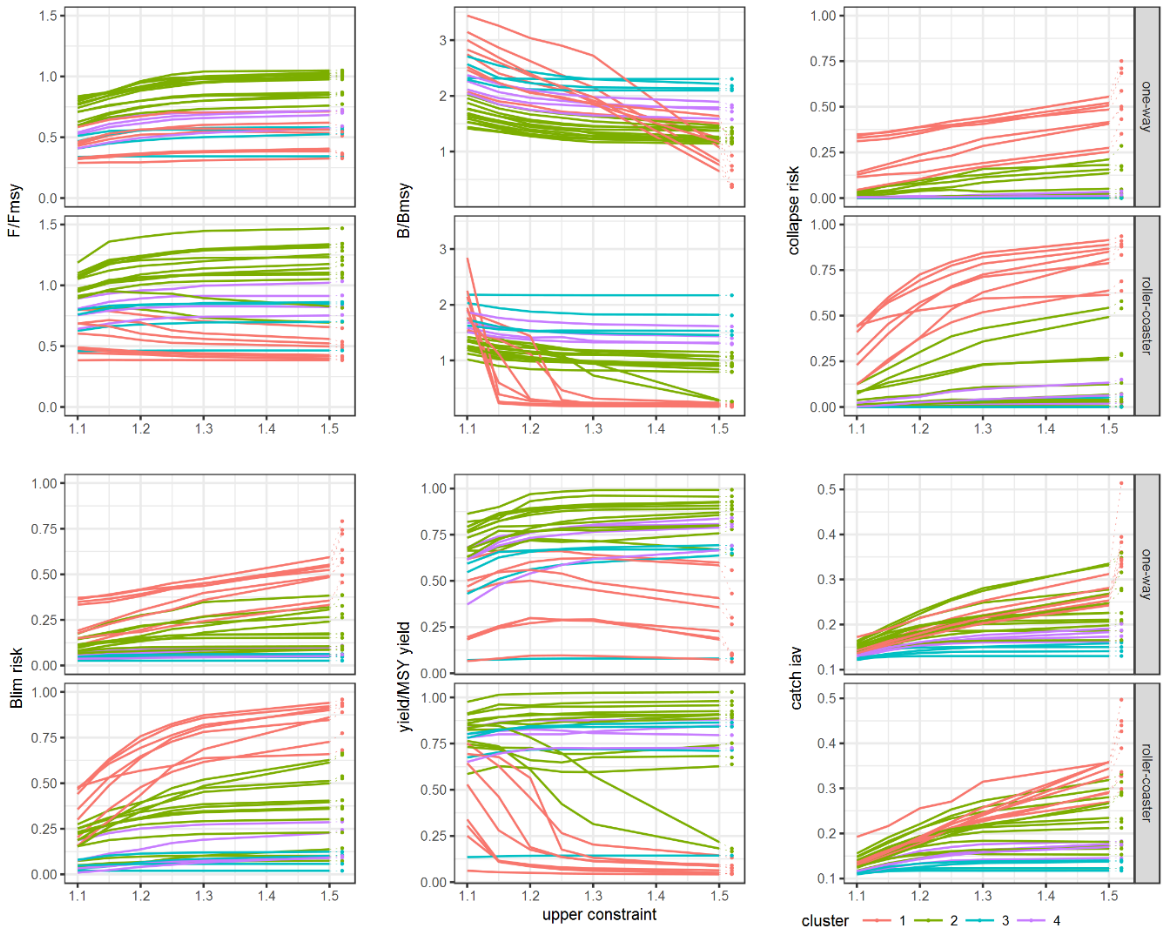

Figure 48. Effect of the implementation of an upper catch constraint on the performance of the catch rule for the 29 simulations stocks.

For most stocks the yield was reduced when upper catch constraints were used. An exception was for the stocks from cluster 1. In the one-way fishing history, the yield peaked at upper constraints between 1.15 and 1.3, and in the roller-coaster scenario, the yield increased up to the most restrictive constraint (1.1). For most of the remaining stocks, the yield is relatively stable for constraints at or above 1.2, and this value seems to be a reasonable compromise between risk reduction and maximising yield.

In general, including a lower constraint on the catch increased the risk of stock collapse and resulted in subsequent reduction in yield. If the lower constraint was implemented in combination with an upper constraint, for some stocks a small peak in yield was observed at lower constraint levels above 0 and below 1. Figure 49 shows the effect of including lower catch constraints on the performance of the catch rule in combination with an upper constraint of 1.2. More restrictive lower constraints (i.e. restricting catch reductions) caused a large increase in risks and this behaviour was particularly pronounced at constraint levels above 0.7. Below 0.7, the risks were relatively stable. A very similar but inverted behaviour was evident for the yield which stays relatively stable (or even slightly increased) up to 0.7 and once the catch cannot be reduced much further, there is a large drop in yield.

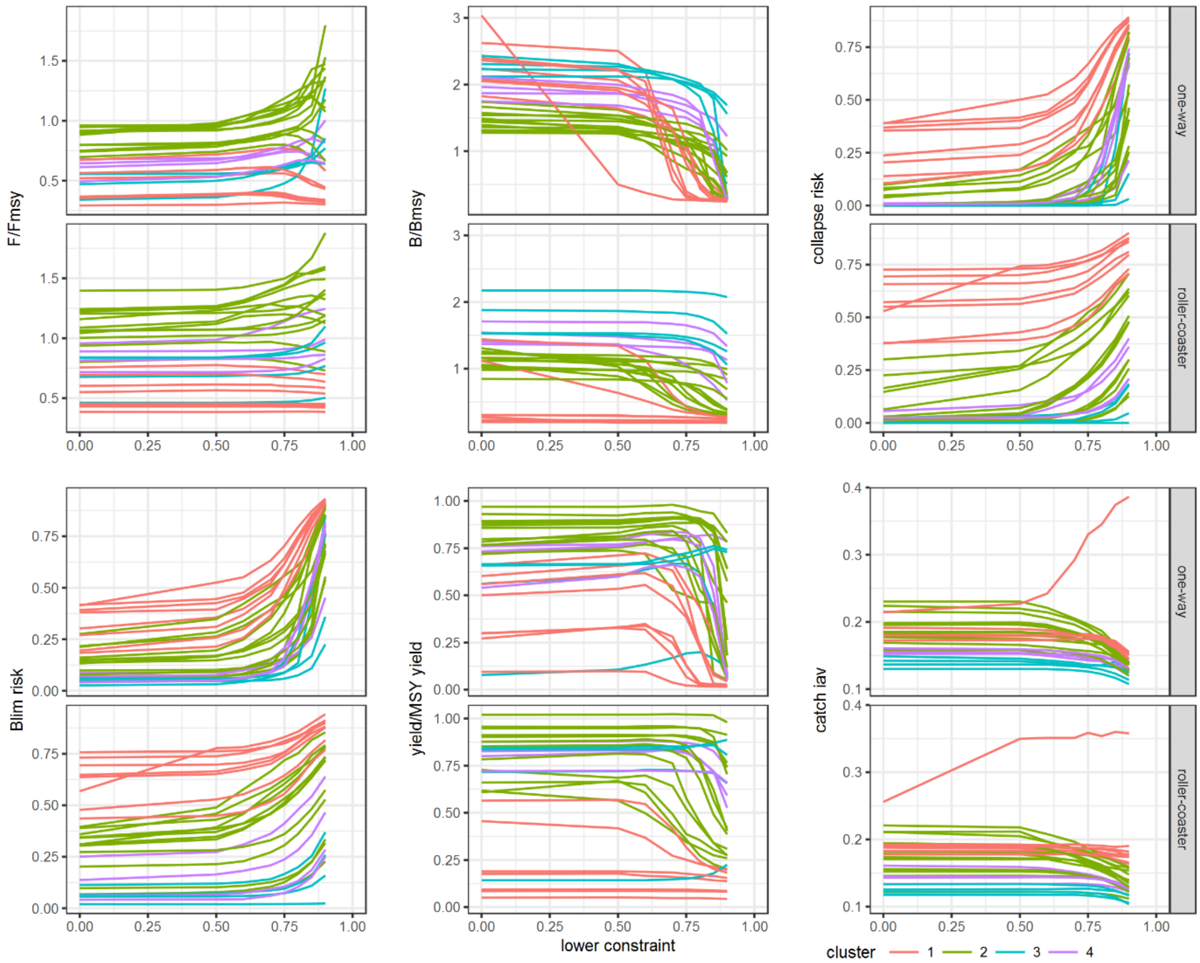

Figure 49. Effect of the implementation of a lower catch constraint in addition to an upper catch constraint of 1.2 on the performance of the catch rule for the 29 simulations stocks.

Data timing

For the stocks surviving the default implementation of the catch rule, using more recent data and giving advice more frequently improved the performance by reducing oscillations and the final biomass values were reached earlier (Figure 50, Figure 51). The lowest fluctuations were observed when the advice was given annually, the catch data provided up to the intermediate year, and the survey data up to the beginning of the advice year. The terminal biomass values were similar irrespective of the timing. Some of the high k stocks (cluster 1, $k \geq 0.38$) could be saved; however, two stocks (jnd and her-nis) still collapsed even if the advice was given annually and the most recent data were used.

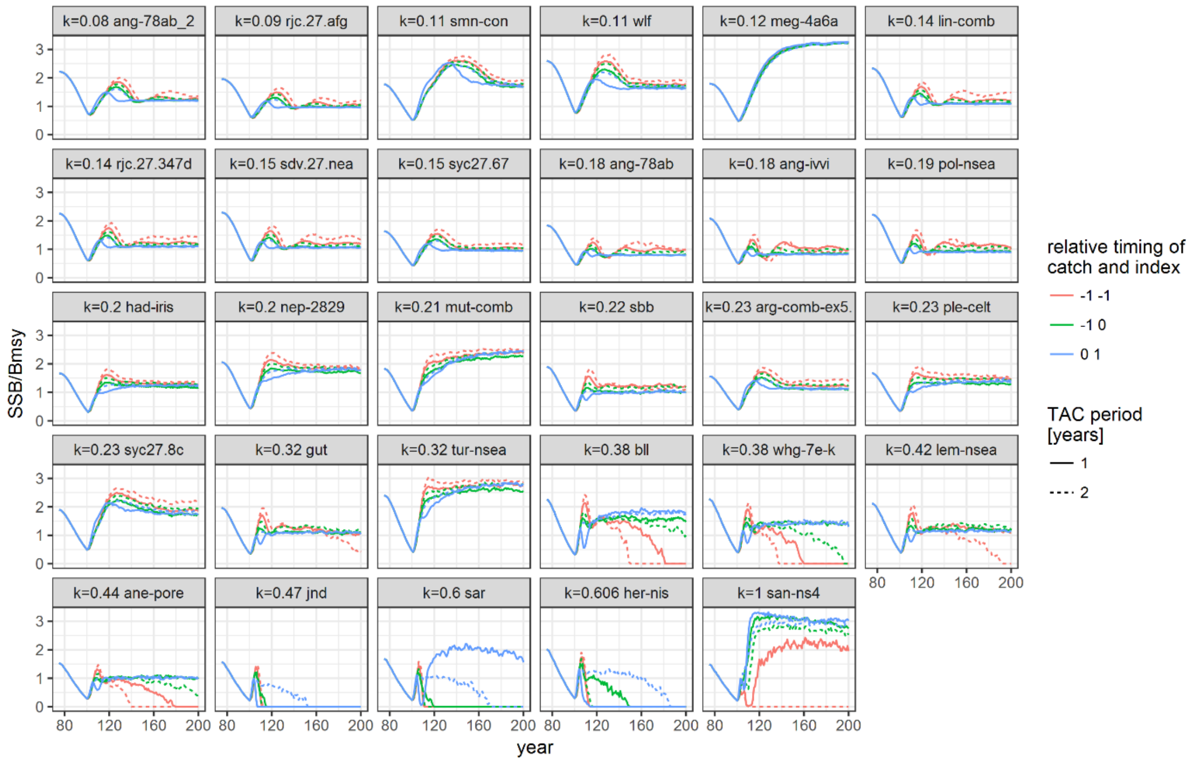

Figure 50. Effect of data timing used in the catch rule on the biomass trajectory for the 29 simulated stocks, sorted by *k*. The values for the timing of catch and index are relative to the intermediate (assessment) year (0), -1 stands for the year before the intermediate year and 1 for the (first) advice year. TAC period 2 relates to biennial advice, and 1 to annual advice.

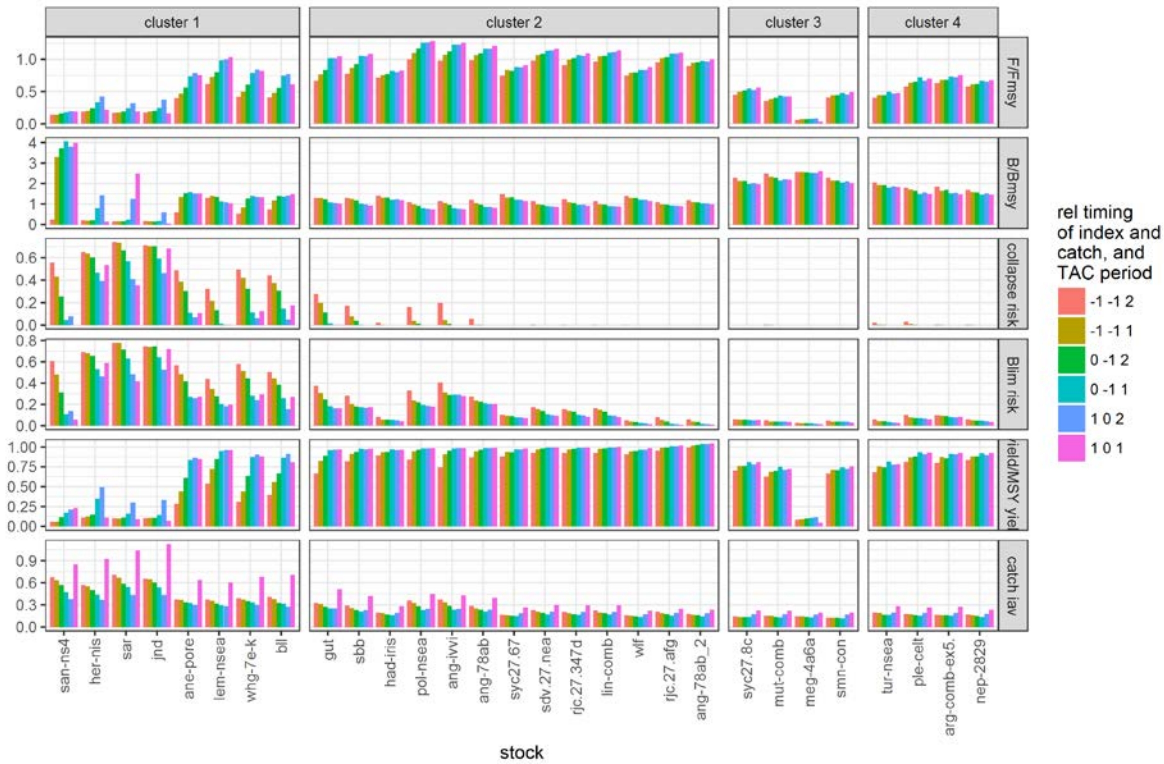

Figure 51. Effect of data timing used in the catch rule on the performance statistics for the 29 simulated stocks. The stocks are grouped in terms of clusters and ordered from high to low *k* within each cluster.

Contribution of the components of the catch rule to the advice

Figure 52 and Figure 53 show the contribution of the individual components (*r*, *f* and *b*) of catch rule 3.2.1 to the total change in catch advice; stocks are ordered from low high to values of *k*. In the first years after the implementation of the catch rule, the catch advice was reduced for all stocks. This was mainly driven by the component *b* (biomass safeguard) but once the stocks recovered, *b* did not have a substantial impact anymore and variation in catches was then mainly caused by *r* (index trend). Overall, f (exploitation status based on mean length in the catch) had the lowest contribution and was often dominated by r. The picture for the high k stocks differs from the remaining stocks and showed a much higher variation in the values of the catch rule components. Component *b* was active for a longer time period after the start of the MSE simulation and more frequently in disagreement with r.

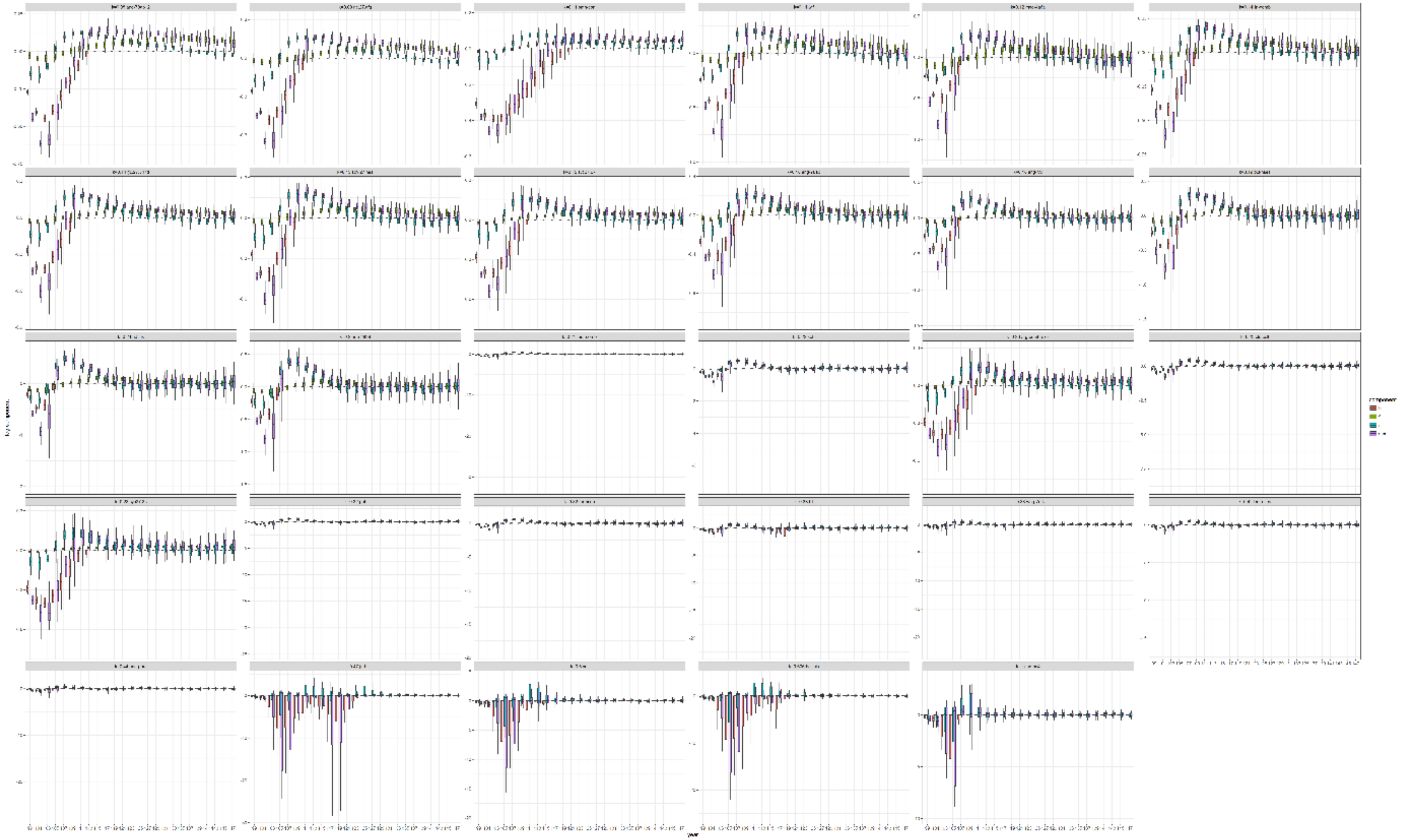

Figure 52. Contribution of the components of catch rule 3.2.1. Shown is the natural logarithm of components *r*, *f*, *b* and their sum for all advice years for all stocks from the one-way fishing history, sorted by *k*. Each boxplot in a given year summarises the distribution of 50 iterations of a component. Outliers outside the boxplot whiskers are removed for better visibility.

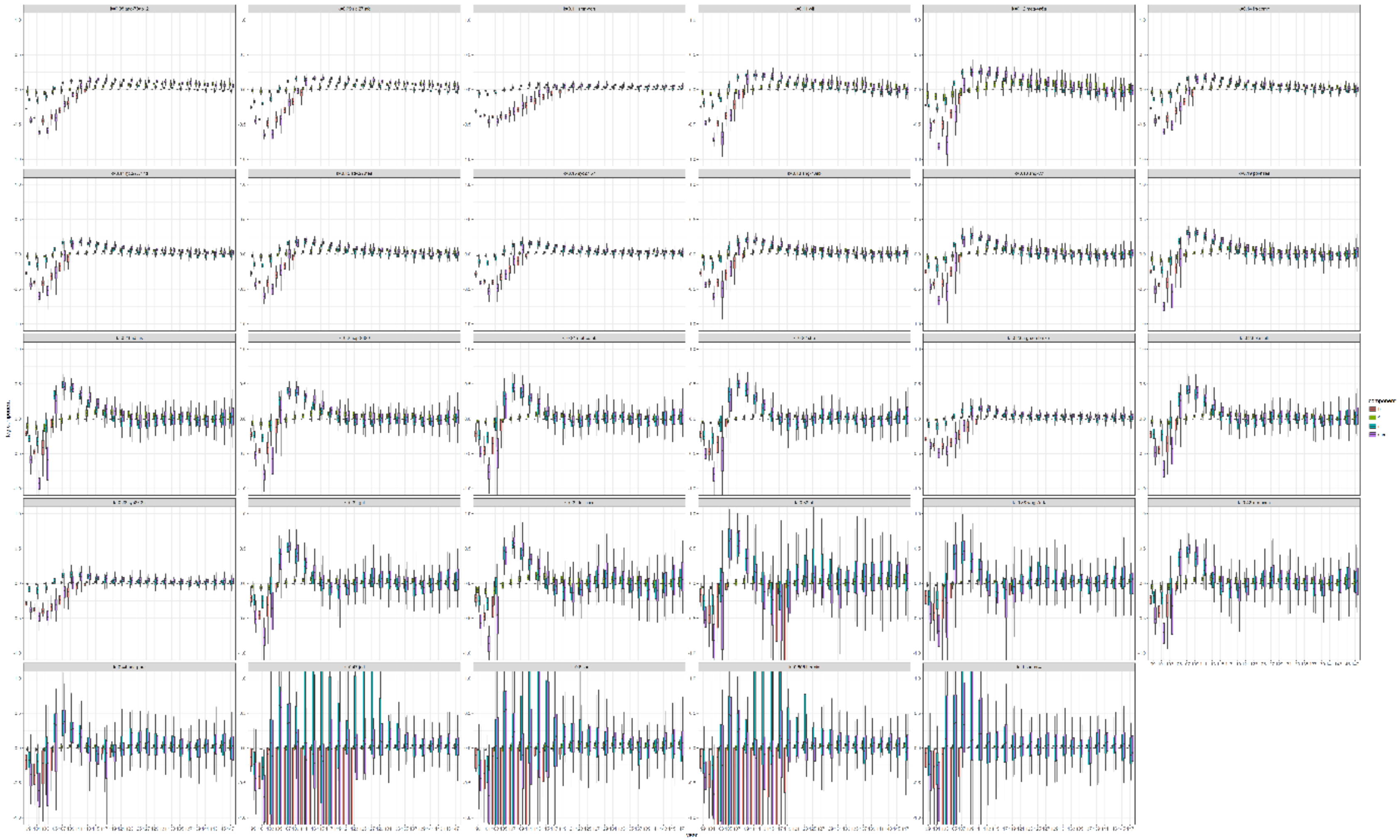

Figure 53. Contribution of the individual components of catch rule 3.2.1. The data shown is the same as in Figure 52 but the y-axis is standardized between all stocks.

Alternative natural mortality in operating model

Implementing alternative *M* formulations changed the behaviour of the stocks when subjected to the catch rule (Figure 54) and the perception was similar for both tested fishing histories. For most stocks, in particular for the ones in the lower to medium *k* range, general trends remained the same. For the higher *k* stocks, implementing Lorenzen *M* led to lower natural mortalities compared to Gislason's *M* and collapses were avoided in many cases.

Figure 55 shows the SSB trajectories for the various Lorenzen natural mortality levels explored. Trajectories were more influenced by the mortality-at-age 20 (M2) and less by the mortality-at-age 1 (M1). In general, higher values of natural mortalities resulted in more pronounced fluctuations and more extreme values, this is because when *M* is increased the proportion of younger age classes in the population increases and so the time-series are influenced by recruitment variability.

Figure 54. Effect of using alternative *M* formulations in the operating model and recruitment variation on the biomass trajectory when the stocks were fished with catch rule 3.2.1, assuming perfect information. Shown are medians for the one-way fishing history and seven different *M* scenarios (one Gislason mortality, six Lorenzen mortalities), each with two different recruitment variabilities (CV=0.3 and 0.6).

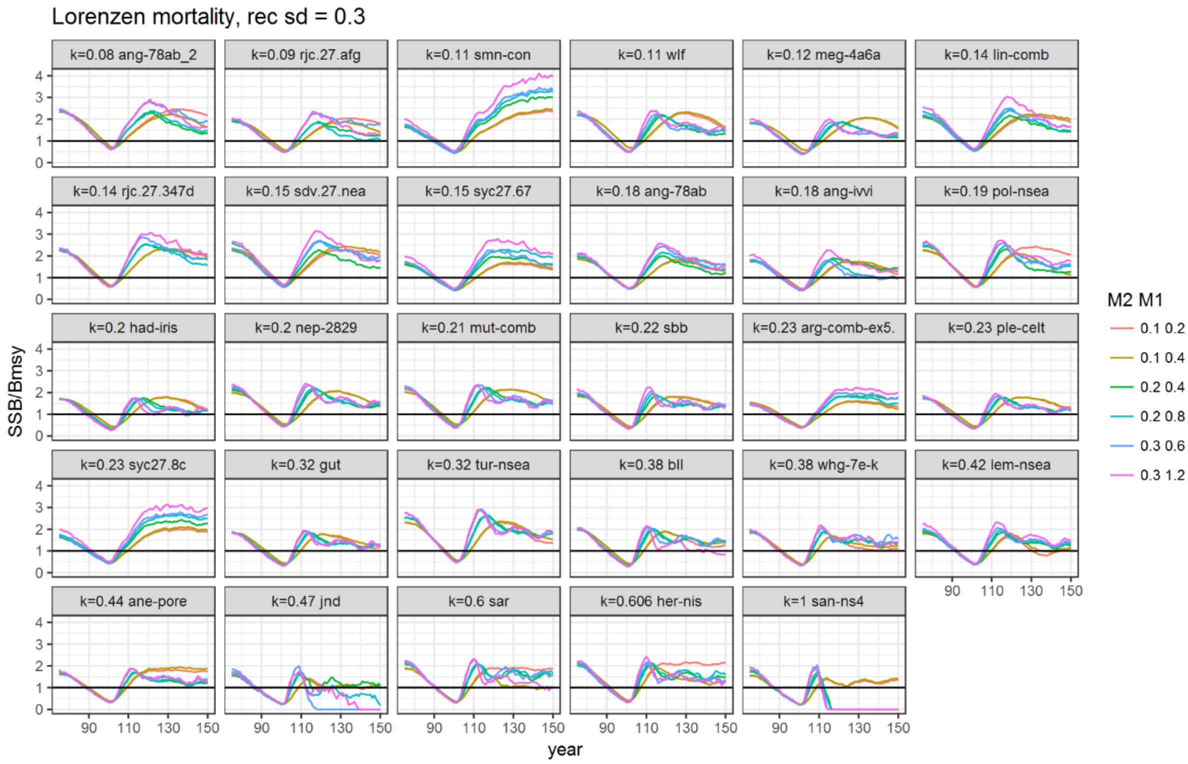

Figure 55. Different parametrisations of Lorenzen natural mortality and the impact on catch rule 3.2.1 in a perfect information scenario for the one-way fishing history. Colour coded are the different natural mortalities, M1 is the natural mortality-at-age 1 and M2 is the (theoretical, in case the maximum age is below age 20) natural mortality-at-age 20.

Perfect information and knowledge scenario

When catch rule 3.2.1 was implemented with perfect information and knowledge (i.e. the SSB from the Operating Model was used as the index and $I_{trigger}$ set to $0.5B_{MSY}$, also from the Operating Model), the performance of the catch rule was substantially improved and most stocks converged towards B_{MSY}, indicating the catch rule works under these unrealistically perfect conditions (Figure 56 and Figure 57).However, stocks with higher k values generally displayed a stronger oscillatory behaviour. Among the high k stocks ($k > 0.32$), three stocks survived (bll, whg-7e–k and lem-nsea) in the one-way fishing history scenario but the remaining stocks, and all high k stocks in the roller-coaster fishing scenario, showed poor performance with collapses. The highest k stock, san-ns4, showed a recovery to very high biomass levels, but this behaviour could be attributed to the fact that this stock was at the brink of a stock collapse, with catches reduced to very low levels, and consequently the stock could recover with (almost) no fishing activity.

Figure 58 shows a correlation plot between the long-term stock levels vs. the level at the beginning of the simulations relative to B_{MSY} for the scenario where $I_{trigger}$ is based on I_{loss}. The results from the correlation analysis revealed that there is a significant positive correlation ($\rho = 0.69$; $p \leq 0.01$), indicating that where stocks ended up was strongly dependent on the starting conditions. This strong dependence was related to the level at which $I_{trigger}$ was set in the historic period of the simulation (i.e. prior to when the catch rule was first applied): too low and the b component of the rule offered no protection and stocks collapsed; too high and it offered too much protection, so stocks overshot B_{MSY} by some margin.

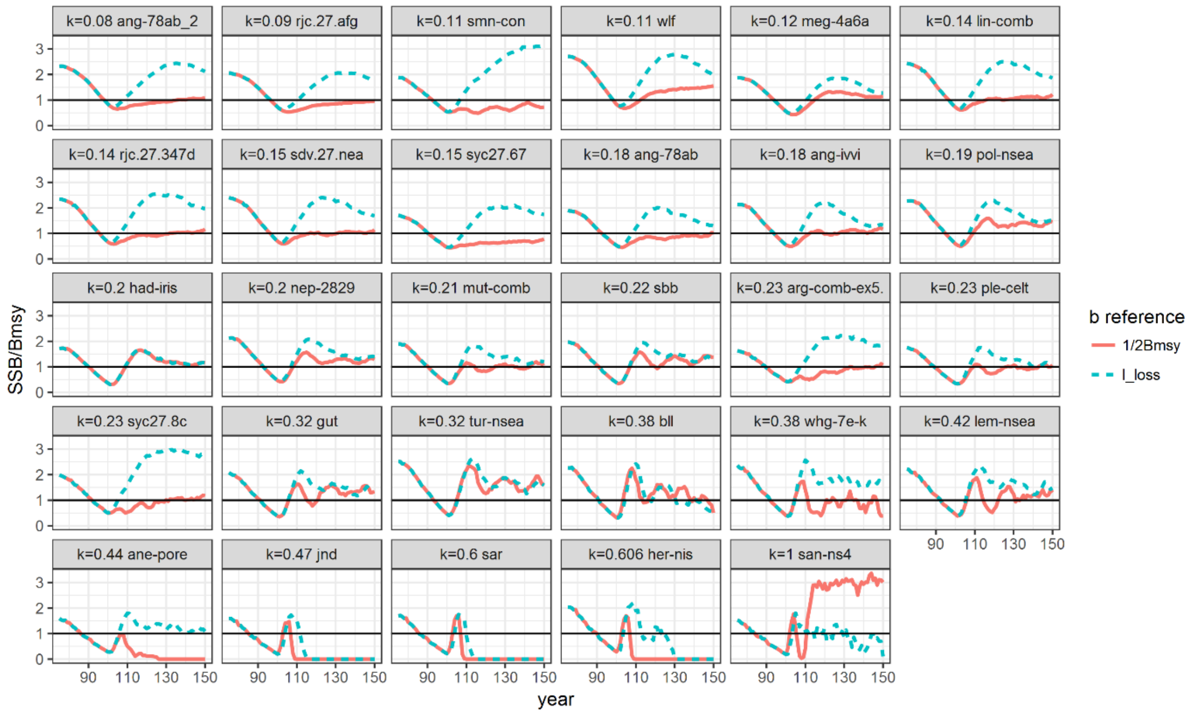

Figure 56. SSB trajectories from catch rule 3.2.1 with perfect information and knowledge (red solid line) compared with the scenarios where $I_{trigger}$ is set to the lowest observed index value (blue dashed line). Shown are the medians for all simulated stocks with the one-way fishing history.

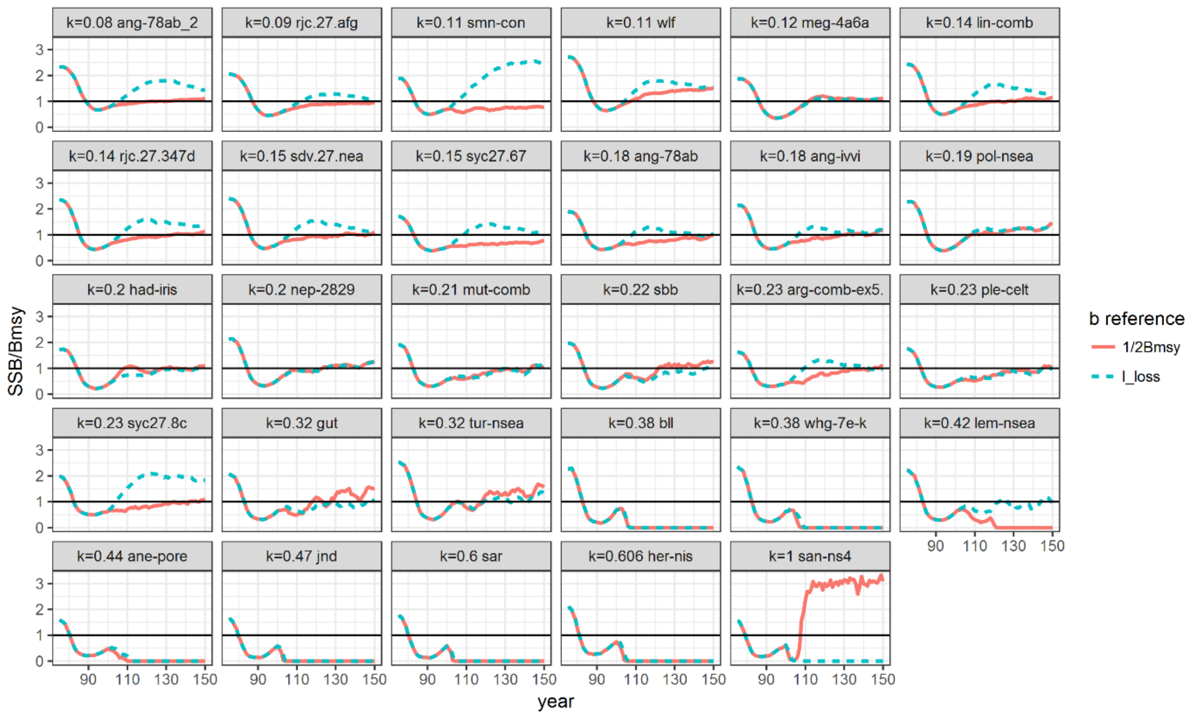

Figure 57. SSB trajectories from catch rule 3.2.1 with perfect information and knowledge (red solid line) compared with the scenarios where $I_{trigger}$ is set to the lowest observed index value (blue dashed line). Shown are the medians for all simulated stocks with the roller-coaster fishing history.

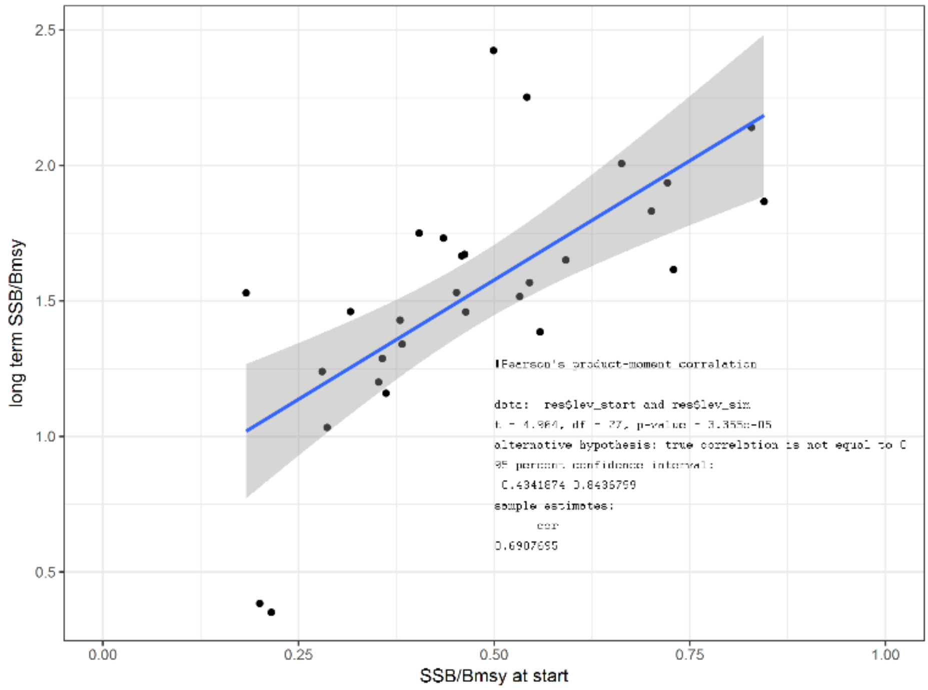

Figure 58. Correlation between the long-term SSB vs. SSB at the beginning of the MSE simulation. The results presented here are for the perfect information scenario for all stocks where the index threshold is defined based on the lowest observed value and for the one-way fishing history (corresponds to blue dashed lines in Figure 56).

Alternative catch rule: catch rule 3.2.2

Result for the two tested $F_{proxy,MSY}$ harvest rates for the one-way fishing history are shown in Figure 59. When the $F_{proxy,MSY}$values were derived from the real F_{MSY}, most stocks quickly converged towards B_{MSY}. Stocks with higher k values (cluster 1 as determined for catch rule 3.2.1) are a notable exception. All but one of them (lem-nsea) collapsed. The alternative estimation procedure for the harvest rate, making use of $L_{F=M}$ to set $F_{proxy,MSY}$, markedly changed the behaviour of the stocks during the simulation. The lower k stocks converged quickly towards their terminal biomass value but this value differed from the one observed with the original $F_{proxy,MSY}$. For stocks where $L_{F=M}$ was larger than the length when the stock was fished at F_{MSY} (L_{MSY}), i.e. the proxy was more precautionary, the stocks ended up at biomass levels above B_{MSY} and vice versa. These results were the same for both fishing histories.

Using more recent data and giving advice more frequently (annually compared to biennially) generally improved the performance of the catch rule and the performance was better the more recent the data were, and when the advice was given annually (Figure 60). For the lower k stocks, the improvement was minimal. Among the higher k stocks, lem-nsea survived even with default timing, two more stocks (whg-7e–k and ane-pore) could be saved simply by giving advice annually, bll required at least data from the intermediate year, jnd required data from the advice year and an annual TAC and the remaining high k stocks could not be saved with any of the tested combinations of data.

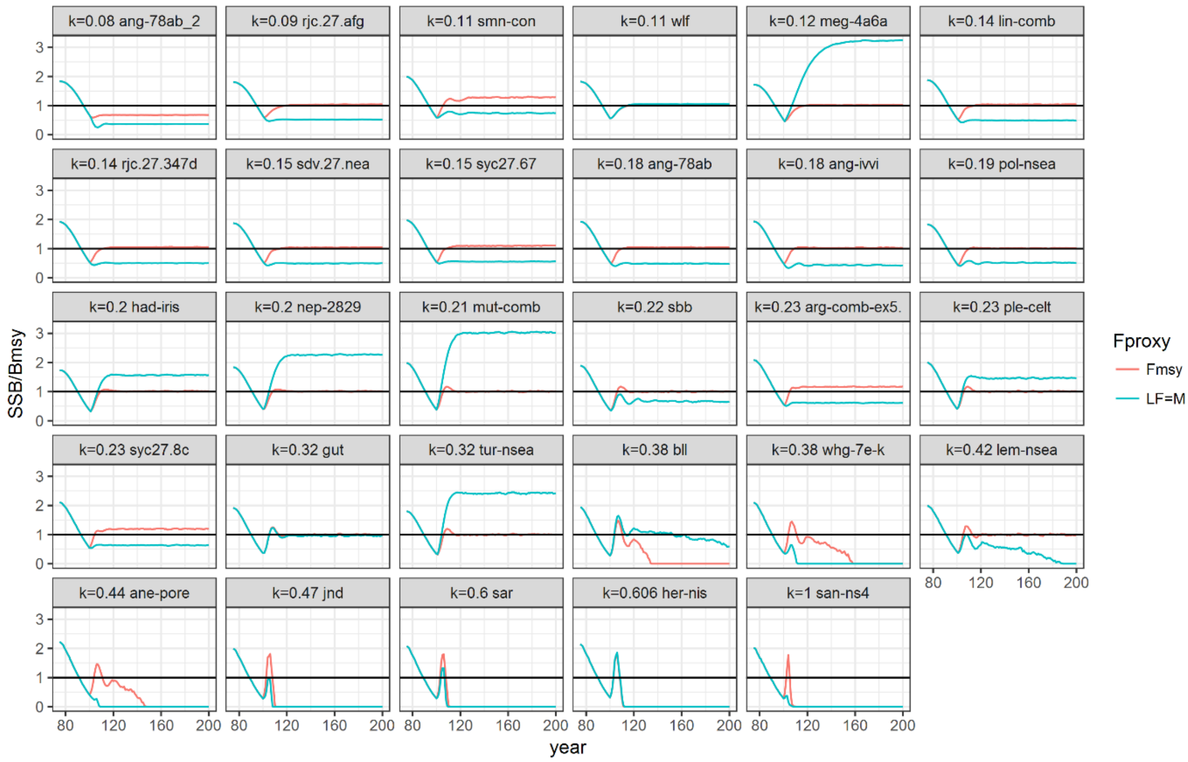

Figure 59. Alternative catch rule 3.2.2 and impact of which $F_{proxy,MSY}$ estimation procedure is used. Shown are the median SSB trajectories for the 29 simulated stocks and the one-way fishing history.

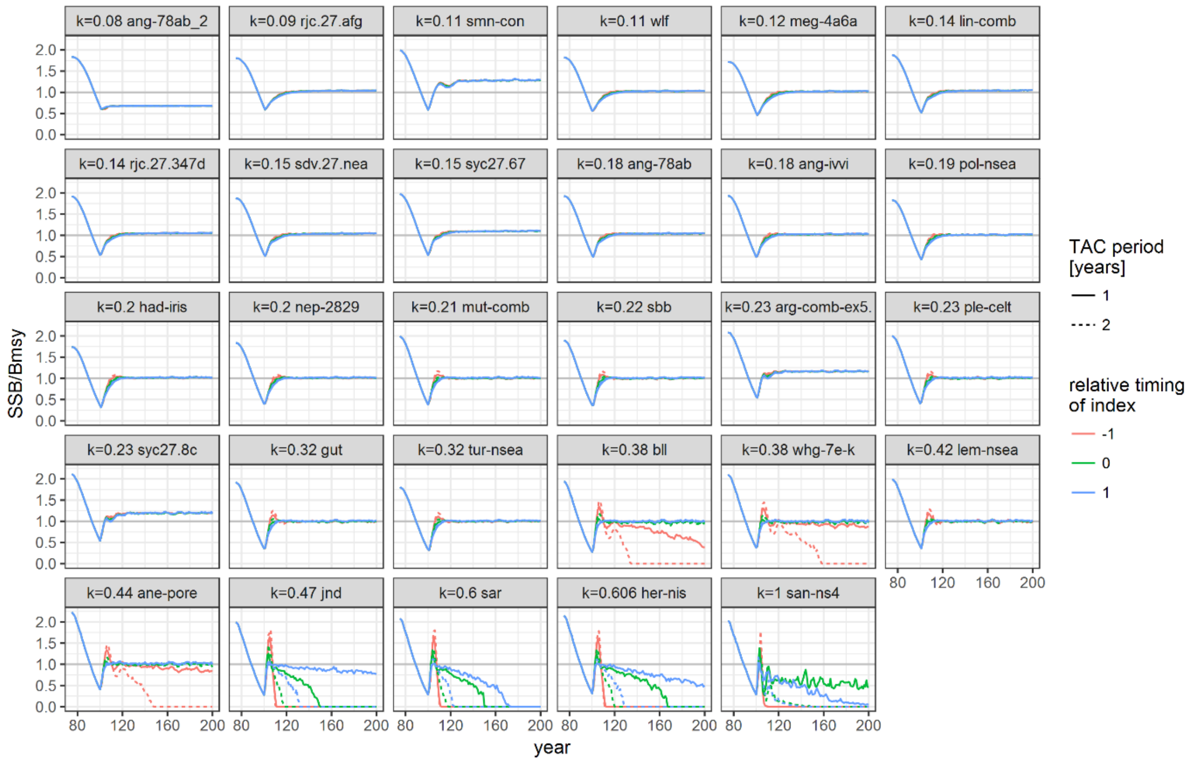

Figure 60. Effect of data timing on the performance of the alternative catch rule 3.2.2. Shown are the median SSB trajectories for the 29 simulated stocks, ordered by k, for the one-way fishing history and for the case where $F_{proxy,MSY}$ was derived from F_{MSY}. The timing of the index is relative the intermediate (assessment) year, -1 indicates data up to the year before intermediate year and 1 up to the beginning of the advice for which the advice is given. TAC period 2 relates to biennial advice, and 1 to annual advice.

Discussion

A visual inspection of the simulation results alone highlighted clear patterns of behaviour across the stocks (see e.g. ICES, 2018), the clustering approach applied here was a useful method for identifying such groupings using an objective and repeatable approach.

Both the clustering analysis and the penalized regression approach indicate that there is a clear relationship between the life histories of the simulated stocks, and the performance of the catch rule. The most important finding is the separation of the simulation trajectories into two groups; one where the stocks collapse during the simulation, and the other where the stocks survive and end up at or above B_{MSY}. The split corresponded well to the von Bertalanffy growth parameter k and the catch rule seemed to perform reasonably for stocks with $k \leq 0.32$, but very poorly for stocks with $k > 0.32$.

The clustering approach adopted here was performed on the SSB trajectories of the simulated stocks relative to B_{MSY}. By using this quantity, the behaviour of the different stocks, when subjected to the catch rule, could be conveniently compared irrespective of absolute stock values.

The general conclusion from the cluster analysis and penalized regression models was that the catch rule should only be considered for stock with $k \leq 0.32$, and most of the subsequent analyses and recommendations focus on these stocks.

Multiplier

The addition of a multiplier below one to the catch rule involved a trade-off between risk and yield: risk improved in all cases, but there was always a loss in yield within each cluster. Although application of the multiplier always reduced the risk, the stocks ended up frequently above B_{MSY}, and the catch rule was overly reactive to minor changes of the multiplier for higher k stocks. For stocks for which the catch rule kept the stock at or above B_{MSY} in the long term, the multiplier moved the stock level further away from B_{MSY} and reduced yield. Stocks which collapsed when the default catch rule was applied could be saved, but only at the cost of moving the stocks far above B_{MSY} and losing yield.

For the stocks for which the catch rule worked (i.e. stocks with $k \leq 0.32$, which on average did not collapse) recommendations on multipliers could be given in terms of risk. For low k stocks ($0.08 \leq k \leq 0.19$), a multiplier of 0.9 ensured, on average (median) a risk below 5% and for the medium k stocks ($0.20 \leq k \leq 0.32$) a multiplier of 0.95 would be required. However, these recommendations have to be treated with care, because a median risk at 5% within each k-grouping inevitably means half the stocks will have a higher level of risk than 5%. When considering the spread of risk values (instead of the median), a more precautionary approach would be to consider a multiplier of 0.8–0.85 (i.e. no more than 0.85) for low k stocks ($0.08 \leq k \leq 0.19$) and a multiplier of 0.8–0.9 (i.e. no more than 0.9) for medium k stocks ($0.20 \leq k \leq 0.32$). Furthermore, if there was limited information on k, and it is only known that k is unlikely to be larger than 0.32, then a general multiplier of 0.8 would ensure no more than a 5% risk of being below B_{lim}. As is the norm with simulation studies, the recommendations are conditional on the assumptions of the MSE. Although some attempt was made to use reasonable values, the uncertainty implemented in the simulations is essentially arbitrary and does not necessarily reflect uncertainty as observed in reality. Changes in the level of uncertainty in the operating model and the simulation will influence the risks, and therefore what would be deemed an "acceptable" level of risk. For this study, 5% was selected for the risk threshold based on what ICES uses.

Catch constraints

The implementation of catch constraints needs to account for the trade-off between risk reduction and yield maximization. An upper limit of 1.2 was deemed appropriate because the long-term yield hardly changed for most stocks if less restrictive constraints were implemented; furthermore, this value provides an important reduction in risk compared to the application of the catch rule without any constraints. For this level of upper constraint, a lower constraint of 0.7 seems to be a suitable choice because implementing more restrictive lower constraints would cause a large increase in risk and a drop in yield; furthermore, less restrictive lower constraints did not have much impact on either yield or risk.

Data timing

As could be expected, more recent data did indeed improve the performance of the catch rules (both 3.2.1 and 3.2.2), mainly by reducing oscillations. However, this approach did not prove successful for the high k stocks and therefore, these stocks should not be managed with such catch rules. If these catch rules were considered for implementation, we would recommend to use more recent data, if available, because these would likely improve the performance of the catch rules.

Contribution of the components of the catch rule to the advice

The analysis into the components of the catch rule revealed some of the weaknesses of the 3.2.1 catch rule. The rule is a product of several components, but is mainly dominated by the trend perceived in the index, frequently masking information from the other components. The biomass safeguard is important to recover the stock above a threshold, but depending on how this level is, it might not be effective enough. The information derived from the different sources (the r, f and b components of the rule, representing a biomass index trend, mean length in the catch relative to an MSY proxy, and the protection element, respectively) does not carry the same weight and therefore weaker components are likely to be overruled. This indicates the need to evaluate the rule with alternative weightings of the various components of the rule.

Alternative natural mortality in the operating model

Implementing various natural mortality assumptions showed a wide spread in the results of the simulations and provided evidence of the uncertainty associated with simulation tasks. However, it has to be stated that the original Gislason natural mortality formulation is likely to be the most realistic. In particular for the higher k stocks, implementing the Lorenzen natural mortality reduced the overall mortality for some stocks, allowing them to grow older (e.g. the sandeel stock with lowest implemented mortality was allowed to grow up to age 30), and therefore crucially altered their life history, changing their dynamics to be closer to stocks simulated with lower k values. Although in some cases unrealistic, this exercise highlighted the impact of the natural mortality assumption on the nature of time-series, and pointed towards focusing effort on developing catch rules that react to the nature of time-series, rather than being developed to depend on life-history parameters *per se*. This is not to say that life-history parameters are not important, because ultimately they govern the nature of time-series, but the key is that it is not always possible to anticipate the nature of time-series from a set of life-history parameters alone.

Perfect information and knowledge scenario

If there is perfect information available, (catch data, survey index, mean length in the catch) and reference points were set correctly according to MSY, then the catch rule performed well and approached the desired MSY target for low-to-medium k stocks. The results from this perfect information and knowledge scenarios showed the importance of setting reference points appropriately, because setting the index trigger value depending on the fishing history based on the lowest ever observed value governed where the biomass ended up. The lowest k stocks were less depleted in terms of depletion relative to B_{MSY}, and therefore the trigger point in the catch rule was higher, which in turn resulted in a higher terminal biomass when the stocks were subjected to the catch rule.

In a real-life application, the stocks for which the catch rule would be considered are data-limited, and consequently reference values are uncertain, possibly impeding the performance of the rule.

Alternative catch rule: catch rule 3.2.2

Catch rule 3.2.2 proved to be an interesting alternative to catch rule 3.2.1. The main difference between them is, that rule 3.2.2 incorporates an absolute target and aims to move the stock directly towards. The setting of such a target is notoriously difficult in reality, and miss-specifying the target could move the stock into a non-precautionary state. If, however, an appropriate target exists, catch rule 3.2.2 will likely outperform catch rule 3.2.1, providing more stability, lower risks, and higher long-term yields, i.e. the management follows the MSY approach more closely. In terms of stocks for which this catch rule should be applied, the split is the same as for catch rule 3.2.1 and only stocks with $k \leq 0.32$ should be considered in the default implementation. If more recent data are available, this limit could be increased slightly.

References

Aghabozorgi, S., Shirkhorshidi, A. S., and Wah, T. Y. 2015. Time-series clustering–A decade review. *Information Systems*, ***53*,** 16–38.

Berndt, D. J., and Clifford, J. 1994. Using dynamic time warping to find patterns in time-series. In *KDD workshop* (Vol. 10, No. 16, pp. 359–370).

Friedman, J., Hastie, T., and Tibshirani, R. 2010. Regularization paths for generalized linear models via coordinate descent. *Journal of statistical software*, ***33*(1),** 1.

Gislason, H., Daan, N., Rice, J. C., and Pope, J. G. 2010. Size, growth, temperature and the natural mortality of marine fish. Fish and Fisheries, 11(2), 149–158.

Hoerl, A., and Kennard, R. 1988. Ridge regression, in 'Encyclopedia of Statistical Sciences', Vol. 8.

Hordyk, A., Ono, K., Sainsbury, K., Loneragan, N., and Prince, J. 2014. Some explorations of the life history ratios to describe length composition, spawning-per-recruit, and the spawning potential ratio. ICES Journal of Marine Science, 72(1), 204–216.

ICES. 2017. Report of the Workshop on the Development of the ICES approach to providing MSY advice for category 3 and 4 stocks (WKMSYCat34), 6–10 March 2017, Copenhagen, Denmark. ICES CM 2017/ ACOM:47. 53 pp.

ICES. 2018. Report of the ICES Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for stocks in categories 3–6 (WKLIFE VII), 2–6 October 2017, Lisbon, Portugal. ICES CM 2016/ACOM:59. 106 pp.

Lorenzen, K. 1996. The relationship between body weight and natural mortality in juvenile and adult fish: a comparison of natural ecosystems and aquaculture. Journal of fish biology, 49(4), 627–642.

Tibshirani, R. 1996. Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society. Series B (Methodological), 267–288.

Zou, H., and Hastie, T. 2005. Regularization and variable selection via the elastic net. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 67(2), 301–320.

Annex 3: Working document - Testing the performance of different catch rules based on survey trends for the management of short-lived category 3 stocks

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A3.1 Introduction

As mentioned in ICES (2012), the underlying idea of survey-based catch advice is based "on Russell's (1931) non-equilibrium definition of overfishing, in which catch exceeds biological production and causes a reduction in the stock. Therefore, decreasing surveys suggest catch should be incrementally decreased and vice versa".

Most of the methods for category 3 stocks advice based on survey indices were developed for stocks with a relative high inertia compared to observation errors in the survey index. As such the 20% uncertainty cap filters observation errors preventing the advice to push the exploitation to unlikely high or low levels[2]. The capacity of an early analysis to determine sustainable F_{MSY} and $MSYI_{trigger}$ proxy levels is capital to allow applying the most comprehensive advice methods such as 3.1 methods.

When an abundance index is available from a direct survey but no proper assessment of F_{MSY} proxies is available then methods 3.2 are by default recommended, whereby:

Equation 1 (method 3.2)

$$\boldsymbol{C_{y+1}} = \boldsymbol{C_{y-1}} \frac{\sum_{y-x}^{y-1} \boldsymbol{I_i}/\boldsymbol{x}}{\sum_{y-z}^{y-x-1} \boldsymbol{I_i}/(\boldsymbol{z}-\boldsymbol{x})}$$

where I is the survey index, x is the number of years in the survey average, and $z > x$. For instance, the case where $x = 2$ and $z = 5$ corresponds to the two-over-three rule, which means taking the average of the last two years' survey indices relative to the three preceding years. The two-over-three rule is the default suggestion for the application of this method. However, the three-over-five rule has been preferred for skates, rays, and elasmobranchs.

C_{y-1} can be either the last year catch or advice (if declining) or the last three years catches (or advices) unless there are justified reasons for using a longer or different time period. Finally, the 20% Uncertainty Cap is applied to the catch advice and if necessary, the Precautionary Buffer.

Alternatively, method 3.3 is applied when the biomass index is increasing or stable over a representative period of time before the trend-based management starts. Then an F_{proxy} can be calculated as the average of a time-series of total catch divided by survey biomass to derive catch advice. The catch advice can be derived by multiplying

[2] WKLIFE VI assessed the uncertainty cap applied to survey index data: "Survey indices, as often used with these stocks, can be quite noisy. If signals go up a lot, it doesn't follow that the stock is really abundant and vice-versa if going down; instead, it could just mean the survey indices are merely tracking noise in the data. A 20 percent cap either way built into the advice takes this into account. Based on their simulations, the 20 percent value for categories 3 to 6 stocks was judged by the group to be appropriate."

the F_{proxy} by I_{y-1} and then applying if necessary, the 20% Uncertainty Cap or the Precautionary Buffer. This can be expressed without the last two optional corrections as:

Equation 2 (method 3.3) $$\boldsymbol{C_{y+1} = I_{y-1} \frac{\sum_{y-z}^{y-1} C_i/z}{\sum_{y-z}^{y-1} I_i/z} = I_{y-1} \cdot F_{proxy}}$$

Certainly, the F_{proxy} is a sustainable harvest rate in terms of the survey index (Hr, catch over survey index). The value z refers to the number of years prior to start the management when exploitation is presumed sustainable. If such ratio (or F_{proxy}) is left invariant in future, the advice comes from applying the sustainable Hr to every year survey index.

In this WD, we focus on the application of these Rules to short-lived category 3 stocks for which an abundance index is available either from one or several surveys, but no proper assessment of F_{MSY} proxies is available. For these species methods 3.2 are recommended, but the high turn-over of the population (low inertia) due to the strong recruitment variability (coupled with the short lifespan of these species) requires a quick reaction of management to survey indications of stock fluctuations. This has often been achieved through an in-year advice just after the survey is carried out as soon as the index becomes available, which required ad hoc modification of the default methods 3.2 and 3.3.

Examples of these modifications are:

a) <u>Sprat in 27.3.a</u>: Method 3.2 is modified for in-year catch advice, based on a comparison of the latest index value with the four preceding values (one-over-four rule), multiplied by the most recent advised catch ($\boldsymbol{C'_{y-1}}$) (ICES, 2017). In this case, the index is a combination of several surveys, including a survey at the beginning of the advice year. The formulation proposed was as follows for a management going from July $\boldsymbol{y}$ to June $\boldsymbol{y+1}$ (Cy) a survey Index during the first half of the year $\boldsymbol{y}$ (Iy) and the prior advice for July $\boldsymbol{y-1}$ to June $\boldsymbol{y}$ ($\boldsymbol{C_{y-1}}$):

Equation 3 (Sprat 3.2 method) $$\boldsymbol{C_y = C_{y-1} \frac{I_y}{\sum_{y-4}^{y-1} I_i/4}}$$

Such advice is constrained by a 20% Uncertainty Cap and a Precautionary Buffer of 20% to be applied every three years unless there is ancillary information clearly indicating that the current level of exploitation is appropriate to the stock (ICES, 2018).

This management started in 2015 and the catch advice to start the management was the actual catch.

b) <u>Anchovy in 9.a</u>: (after WKPELA 2018 (ICES, 2018)), a modification of method 3.2 was proposed for the in-year advice on sustainable catches: The in-year catch advice (Cy) for the management period July to June will be based on the multiplication of the latest advice on catches by the one-over-two ratio of the recent survey indices. This one-over-two rule set the Cy advice from July y to June y+1, based on a survey Index during the first half of the year y (Iy) and the prior advice for July y-1 to June y ($\boldsymbol{C_{y-1}}$), as follows:

Equation 4 (Anchovy in 9.a) $$\boldsymbol{C_y = C_{y-1} \frac{I_y}{\sum_{y-2}^{y-1} I_i/2}}$$

In fact, this advice was provisionally set to be constrained by a 20% Uncertainty Cap (no Precautionary Buffer was necessary as exploitation seemed sustainable in the past).

The issue of the 20% uncertainty cap was also object of debate in WKPELA. It was advocated that there is no need to apply the 20% uncertainty cap for various reasons: i) As for these short-lived species with rapid changes in biomass, the biomass of reference for an in-year advice should be the biomass of the current year for the advice whenever available (and this is actually the information available for the Anchovy), such information removes much of the uncertainty about the current status of the stock concerned by the advice. ii) for a population having very large interannual variability (far larger than 20%), the uncertainty cap would lead to undesirable situations of too restricted upward catch advices at rapid stock booms, but to insufficient reductions of catches at bust situations (with the risk of depletion of the stock). WKPELA 2018 asked for application of the 20% uncertainty cap because this was the standard in the ICES approaches for category 3 stocks. However, it was admitted that "it is considered that 20% uncertainty cap might not be appropriate to short-lived species. Therefore, this procedure should be evaluated for this kind of species. An appropriate forum would be WKLIFE VIII taking place in 2018".

In addition, in WKPELA2018 some debate occurred around how many years of Survey indicators should be averaged for the numerator and denominator of the survey ratio rule. To account for the rapid population fluctuations, both Sprat and Anchovy selected to use only the latest survey index in the numerator, but for the denominator a mean of the prior four and two years were respectively selected. The reasons are unclear but are partly related to the capacity to follow the fluctuations of the stock by the advisory rule conditioned by the 20% uncertainty cap.

Finally the issue of what initial Catch ($\boldsymbol{C_{y-1}}$) is to be used to start the series of provision of catch advise based these advisory rules is not defined anywhere but it is likely that may have a non-negligible role in the performance of the rule as it conditions the initial harvest rate to be applied to the future exploitation of the stock. For anchovy this was just taken as the most recent prior catch during the management period.

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The purpose of this work is to evaluate the performance of different Catch rules (HCRs) in line with methods 3.2 and 3.3 applied by ICES (ICES, 2012) for the in-year management of category 3 short-lived stocks. In particular, the objective is to test whether for in-year advice, the one-over-two or one-over-three methods outperform the other two-over-three or three-over-five rules, and at the same time to assess whether the uncertainty cap of 20% is advisable or if a weaker or none uncertainty cap should be selected for these advisory rules for in-year advice.

The selection of the optimal advisory rule between methods 3.2 or 3.3 relies on the perception of the sustainability of the past exploitation of the stock and the capability of assessing any F_{MSY} proxy (F_{proxy}). We will focus on stocks presumed to be sustainably exploited in the past but where no clear F_{MSY} proxy is available. The general hypothesis is that the InterAnnual Variability (IAV) of the stock biomass series vs. the observation errors determines the performance of the advisory rules, only based on trend-based analysis. We will compare the performance of the one-over-Nyears rules (for N 2 and 3) and two or three-over-Nyears (for N 3 and 5) (methods 3.2) and a rule with an F_{proxy} (of sustainable harvest rates over N past years) (methods 3.3) for a range of ratios of observation errors over IAVs and for a range of uncertainty cap values.

A3.2 Methods

The performance of different catch rules was tested using Management Strategy Evaluation (MSE). The IAV is the Interannual variance of biomass between consecutive years (in log scale) in the time-series of an unexploited population. This is related to stock life-history parameters such as natural mortality, growth and year-to-year variability of recruitment. We will select one anchovy like stock. The example is taken from anchovy in 9.a. See the parameters selected in Table3.1 to simulate this stock.

The population model is based on an age-structured population, with half-yearly time-steps under the following assumptions.

0–6+ age groups.

Invariant natural mortality (may change between ages) and may have (If desired) interannual random variability common to all ages. This together with Recruitment variability contributes to interannual natural variability. So far Natural mortality has been kept constant in the time-series (no random variability).

Growth: mean weight-at-age in catches and stock (from surveys). In principle it can be subject to interannual random variability as defined by a CV by ages, but in this case given that no analytical assessment will be available these parameters were fixed.

Maturity-at-age, fixed values over time.

Stock–recruitment relationship based on hockey-stick. The lognormal random variability around the expected S–R function is a capital component of the IAV. We assume no autocorrelation in recruitment variability. This (together with natural mortality variability, if allowed) is the main source of natural variability determining IAV.

Invariant fishing selectivity-at-age along time was used to produce the catch according to an $F_{multiplier}$. This goes on half year basis and therefore the % of catches corresponding to the first and second half of the years are set (as a fixed parameter) for all simulations. In addition, the selectivity by age in both halves of the year were identical (except for age 0 which is 0 from January to June).

The observation model generates a Survey index at the desired time of the year, subject to a catchability factor (Q=3 for anchovy and Q=1 for sardine) and to selectivity by age for the survey.

Notice that the amount of information regarding the spawning and the exploited stock in the management year are themselves major variables conditioning the performance of any harvest rule. The first variable refers to whether the survey information contains information about all age classes affecting the managed SSB or just the survivors from last year SSB (i.e. having or lacking information on the next year recruits to SSB). While the second variable refers to the amount of information in terms of the age classes covered by the survey index which will be exploited in the management. By default, we will start with the typical situation of short-lived species where the survey assess age 1+ in the first half of year ***y*** to provide indication of population biomass of ages1+ (not necessarily equal to SSB) to serve as source of advice for the second half of year ***y*** and first half of year ***y+1***. Other scenarios in terms of survey information content will only be studied once covered the first case proposed before.

For the time being, we will assume that there is a single survey with a partial catchability at age 1 (around 0.7 for the anchovy 9a) and a common catchability for all ages 2+, and a random yearly observation error affecting equally all ages.

Biomass Observation errors are typically assumed to have a CV of about 0.25. We first run an analysis for the typical CV of 0.25 on all selected HCRs, then we will run a sensitivity test for a range of CV at 0.5, 1 and 2 times the IAV. These will be lognormal errors. For the case of the anchovy in 9.a the 0.25 log sigma corresponds to a ratio (IAV/ObsError) of 0.7.

Further definition of the Inputs appears in Table3.1 for this Anchovy like stocks. Anchovy 9.a conditioning was made according to the Gadget modelling adopted in the last benchmark of this species (although this is not taken as an absolute assessment of biomasses, that is the reason for setting it as category 2 stock) (WKPELA 2018).

Conditioning the starting populations: The starting population derives from an initial run of the population and the survey for 20 years, being fished at selected harvest rates, subject to random variability (in log scales with a sigma of 0.2). Certainly, the characteristics of the starting population in terms of past exploitation levels and the number of years is itself a variable probably deserving each a sensitivity test to the performance of the management system. We decided to run two scenarios by harvest rates levels: one at level well below F_{MSY}, and another at a higher harvest rate level (around deterministic estimates of F_{MSY}) close but below the fishing mortality leading the biomass in stationary condition to a level close the SSB inflection point.

Harvest Control Rules: The catch rules are all for in-year based management and are grouped as follows:

- Trend based methods (methods 3.2) of the types one-over-Nyears or two-over-N year rules or three-over-Nyears (for N going from 1 to 3) (methods 3.2). This trend-based rules will be called as T1/2, T1/3, T2/3 and T3/5 respectively with the quotients referring to the numbers of years in the numerator and denominator respectively. This cover the most used formulations of this method 3.2. The generic formulas of the method for Tx/z for in year advice appears below:

  Equation 5 $$\boldsymbol{C_{y+1}} = \boldsymbol{C_y} \frac{\sum_{y-x}^{y} \boldsymbol{I_i}/(\boldsymbol{x}+\boldsymbol{1})}{\sum_{y-z}^{y-x-1} \boldsymbol{I_i}/(\boldsymbol{z}-\boldsymbol{x})}$$

  These are blind rules where the actual harvest rates will be changing gradually in time, according to the indicators of the current situation of the stock compared to the past.

- Harvest rate methods (or F_{proxy}) (methods 3.3). This will be called generically as Hr(N), where N refers to the number of years used to make the average of the sustainable harvest rate. The number of past observed sustainable harvest rate may be a factor conditioning the future performance of these harvest control rules, but we will start just by adopting the case of Hr(20). This means that exploitation over the initial starting population is itself considered sustainable. The range of years over which define the F_{proxy} is kept fixed throughout the 20 years simulation period (so the mean of the harvest rate over the starting population (MeanStHr) is the F_{proxy} is applied over the 20 year management period. The generic formula appears below for N years between z and x in the prior period:

  Equation 6 $$\boldsymbol{C_{y+1}} = \boldsymbol{I_y} \frac{\sum_{y-z}^{y-x} \boldsymbol{C_i}/(\boldsymbol{z}-\boldsymbol{x})}{\sum_{y-z}^{y-x} \boldsymbol{I_i}/(\boldsymbol{z}-\boldsymbol{x})}$$

The former HCRs can be affected by an uncertainty cap (UnCap%). We will cover 20%, 50% and 80% uncertainty cap levels (UC) and unconstrained (termed here as the 100%) versions of the former rules.

No initial Precautionary Buffer is considered in the simulations.

The MSE Simulations are run in an Excel Workbook with VBA macros. Each scenario is run for 250 populations.

Performance indicators

Assuming that the fishery has been harvested sustainably in the past, and in the absence of any assessment of F_{MSY} or $MSYB_{trigger}$ proxies, the major performance indicator must be related with the capacity of the rules to sustain the population harvested within historical harvest rates, without exceeding the 95% probability intervals of the historical mean harvest rate (i.e. roughly not exceeding the meanHr +/- 2 sigma of the past Hr variability). This indicator will assess any potential trend in exploitation harvest rates as well.

Other relative performance indicators would be the evidence of any trend to the stock biomass, or to the catches. This is measured here as the mean of the resulting ratios of the entire 20 years managed period or of the last ten years of the simulation period over the entire 20 years of pre-management period.

We also assessed for each simulated initial population the risk of falling below the actual B_{loss} and $B_{loss}/1.4$ of the first 20 years unmanaged population. In addition, an indicator of the risk of falling below B_{lim} (as pointed out by the inflection point of the adopted hockey-stick relationship) is estimated. The Risks so far are of type 1 (the average of yearly risks over a selected period). See further details in the output tables.

The complete set of indicators follow:

- Stock indicators: SSB, SurPopulation and Survey Index.
- Catch indicators: TAC; standard Deviation of the Catch, Realized Catch.
- Exploitation Indicators: F_{bar} (1–2); Hr (SSB); Hr(SurPop); Hr(IndexY).
- Risks of trespassing the past limits (during the initial 20 year simulated populations):
    - Prob(BelowMinSSB) / Prob(BelowLowerSSB) / Prob(BelowB_{loss}/1.4?)
    - Prob(AboveMaxSSB) / Prob(AboveUpperSSB)
    - Prob(AboveUpperHrSSB)/ Prob(AboveMaxHrSPopY) / Prob(AboveUpperHrSpopY)
    - Prob(BelowMinHrSPopY) / Prob(AboveMaxHrIndexY)/ Prob(AboveUpperHrIndexY)
    - Prob(BelowMinHrIndexY)
- Absolute levels of Risks vs. The simulated base population:
    - Prob(BelowB_{lim}, taken as the inflection point)
    - Probability of Collapse (defined below the 10% of the virgin biomass B_o)
- Trends of the management period over the starting unmanaged harvested population:
    - TrendSSB? / TrendHr(SSB)? / TrendHr(SPopY)? / TrendHR(IndexY)?

A3.3 Results

Anchovy in 9.a

Extract of the general results are presented in Table3.2 and Table3.3 to this Annex (tables for healthy starting population and for highly starting exploitation level respectively).

Figures 1 to 4 summarise the typical outcomes in terms of mean tendencies over the 40 years simulated period (20 unmanaged and 20 managed years). Performance indicators appearing in Figures 1 and 2 correspond to T(1/2) applied to a population being sustainable harvested with 20% and for another with No Uncertainty Cup constrained respectively. For the case of 20% Uncertainty Cap, harvest rate values occasionally explode to very high values, corresponding to the occurrence of populations collapses occurring when too high catch values are allowed at very low stock sizes. As a result of this, harvest rates and Fishing mortality increase, despite reducing average catches when the 20% UnCup is applied, while they decrease when no uncertainty cap is applied. Figures 3 and 4 correspond to the high harvested starting population and for them the same pattern is observed.

For the complete range of scenarios analysed, Table 1 shows the resulting biomasses for the management period for the sustainably and heavily exploited strategies for the starting populations… The table HCR T(2/3), T(3/5) and MeanHistorical_HR lead to lower SSB in the management period than HCRs T(1/2) and T(1/3). For the latter HCRs, it is clearer the poorer performance of the 20% UnCap (as it result in lower biomasses). No major differences induced by ratio ObsError/IAV, except for some increase in biomasses for the ratio of 2 which leads to some higher biomasses.

Table 2 show the results in terms of TAC over the management periods. Higher TACs are allowed on average for HCRsT(2/3) and T(3/5) and MeanStHR vs. lower catches on T(1/2) and T(1/3), which gives an explanation to the former results in terms of SSB. The larger the ratio ObsError/IAV, the poorer the catches allowed. Finally, notice that lesser TACs are allowed for the 20% UnCap in T(1/2) and T(1/3), and at the same time they led to smaller mean biomasses. This is again related to the larger probability of collapses (see below).

Table 3 summarises the results in terms of associated Harvest rates to each HCR. There we can see that there are several cases with unrealistic mean high values of harvest rates, which correspond to the occurrence of some cases where the stock collapsed. This increased largely the means of the harvest rates. Those cases are not unusual when the starting population is exploited at a rather high harvest rate close to the deterministic F_{MSY}.

Regarding the ratio ObsError/IAV and the Uncertainty Cup levels, for both starting harvest rate levels and for any Harvest Control Rule, the performance is better the smaller the Ratio of the observation error over the IAV is, and the larger the Uncertainty Cup is. In general, the 20% UnCup invariantly leads to some cases of population collapses (the exact percentage is not yet quantified here), even where the initial population was being sustainably harvested (except for the constant harvest rate, MeanStHR, when the ratio ObErr/IAV is low). In the case of a Starting Population being highly harvested the Uncertainty Cups of 20% and 50% never achieve a sustainable harvest rate level (and are prone to collapse the population) while the 80% and the No Uncertainty Cup conditioning (termed as 100%, i.e. 1 in the Table), are the only ones which can lead to sustainable harvest rates for some HCRs. In Terms of Biomass Table 1 showed that the latter methods are the ones leading to higher biomass levels.

Regarding the Harvest Control Rules, T(1/2) and T(1/3) are the ones performing the best, as T(2/3) and T(3/5) do often lead to unsustainable high harvesting situations. In particular for the starting Population being highly harvested, T(1/2) and T(1/3) are the ones leading to sustainable harvest rates around 0.3 for the last ten years of the managed period (right table panels in Table 3). Furthermore T(1/2) Unconstrained (no Uncertainty Cup) is the best one in leading to sustainable harvest rates for both the first and last ten years of the management period. This means that the HCR which best accommodates to these highly fluctuating resources are those capturing the most recent trends from surveys.

Finally, using the Mean past Harvest rate as an F_{proxy} for method 3.3) shows a consistent result except for the case of very high Observation Error, where the performance worsens and leads to some cases of stock collapse too.

For all cases it is remarkable that for very high observation errors compared to the IAV (i.e. ratio of 2 in the table), then all variable in time HCRs (T(1/2)…. T(3/5) will lead to a continuously decreasing Harvest rate.

The text table below shows the benefits in terms diminishing the risk of stock collapse (risk of falling below 10% of B_0) for the HCR T(1/2) for the two harvesting strategies on the starting population, when no Uncertainty Cap is set compared with the 20% uncertainty Cap:

		T(1/2)	T(1/2)	T(1/2)	T(1/2)
Init HR	UnCap	**0.2**	**0.5**	**0.8**	**1**
0.3	Prob(Collapse1) (20 Years)	0.027	0.000	0.000	0.000
0.6	Prob(Collapse1) (20 Years)	0.203	0.045	0.0374	0.0374
0.3	Prob(Collapse2) (Last 10 Years	0.040	0.000	0.000	0.000
0.6	Prob(Collapse2) (Last 10 Years	0.2372	0.0216	0.0176	0.012

Tables 4 and 5 show rather similar results as shown before, but referring here to the Probability of exceeding past Harvest rates on the Survey population and to the Probability of falling below the Minimum spawning biomass observed in the past over the initial 20 years of unmanaged population respectively. In the first table, it is shown: High probability with T(2/3) and T(3/5) of exceeding past harvest rates / Good performance of T(1/2) and T(1/3) for any ratio of errors / The poorest performance on 20% UnCap for any HCR compared with other Uncertainty Cap levels. For the last table, concerning the risk of falling below minimum past observed biomass levels: it is evidenced the Lower risks at T(1/2) and T(1/3) compared with T(2/3) and T(3/5). Higher ratio ObsError/IAV leads to just slightly higher risks. For T(1/2) and T(1/3) the lesser the UnCap, the lower the risk and for T(2/3) 50% and 80% lead to lower risk levels than 20% or No UnCap.

Table 1. Mean Spawning Biomass in the 20 and last ten years of the management period, according to the ratios of Observation Error over IAV (Columns) and by Harvest Control Rules and Uncertainty Cup levels (Rows), for two cases of harvest rates on the initial (starting) population prior to management: for the healthy starting population (Upper tables) and for the highly exploited starting population (Bottom tables). Uncertainty Cup of 1 means that there is no Uncertainty Cup constraint. MeanStHR means that the Starting mean Harvest Rate is taken a constant F_{proxy} for the future management of the population.

Time Period	21-40	Entire Management Period		
Mean Starting HarvestRate	0.3	Mean Starting SSB		
				1,965
Promedio de Mean SSB	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	1,913	1,938	1,914	1,908
0.5	1,954	1,933	1,935	1,902
0.8	1,953	1,958	1,959	1,947
1	1,933	1,878	1,823	1,648
T(1/2)				
0.2	1,946	1,991	1,968	2,003
0.5	2,095	2,124	2,145	2,254
0.8	2,069	2,096	2,201	2,330
1	2,015	2,023	2,083	2,202
T(1/3)				
0.2	1,962	2,027	2,023	2,081
0.5	2,141	2,159	2,195	2,304
0.8	2,099	2,129	2,187	2,373
1	2,044	2,062	2,083	2,224
T(2/3)				
0.2	1,943	1,896	1,837	1,875
0.5	1,955	2,004	1,956	2,054
0.8	1,886	1,941	1,934	2,046
1	1,842	1,839	1,798	1,682
T(3/5)				
0.2	1,834	1,797	1,816	1,805
0.5	1,794	1,778	1,800	1,826
0.8	1,740	1,670	1,679	1,839
1	1,663	1,585	1,630	1,447

Time Period2	31-40	Last Ten years		
Mean Starting HarvestRate	0.3	Mean Starting SSB		
				1,923
Promedio de Mean SSB2	Obs Error/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	1,967	1,935	1,904	1,900
0.5	1,961	1,918	1,951	1,905
0.8	1,954	1,970	1,947	1,957
1	1,942	1,889	1,808	1,587
T(1/2)				
0.2	1,977	2,019	1,994	2,040
0.5	2,235	2,281	2,308	2,448
0.8	2,169	2,213	2,338	2,518
1	2,093	2,132	2,189	2,407
T(1/3)				
0.2	1,967	2,073	2,092	2,131
0.5	2,257	2,333	2,366	2,509
0.8	2,221	2,260	2,333	2,554
1	2,163	2,168	2,232	2,461
T(2/3)				
0.2	1,986	1,913	1,824	1,859
0.5	2,005	2,063	2,036	2,140
0.8	1,961	2,016	2,001	2,240
1	1,867	1,870	1,811	1,736
T(3/5)				
0.2	1,777	1,769	1,808	1,766
0.5	1,818	1,815	1,837	1,859
0.8	1,698	1,679	1,655	1,899
1	1,604	1,535	1,577	1,340

Time Period	21-40			
Mean Starting HarvestRate	0.6	Mean Starting SSB		
				1,279
Promedio de Mean SSB	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	1,043	1,110	1,032	1,122
0.5	1,110	1,137	1,212	1,139
0.8	1,151	1,143	1,093	1,145
1	974	937	918	767
T(1/2)				
0.2	1,318	1,274	1,273	1,340
0.5	1,547	1,479	1,530	1,660
0.8	1,526	1,607	1,691	1,916
1	1,450	1,377	1,509	1,685
T(1/3)				
0.2	1,295	1,293	1,385	1,439
0.5	1,530	1,575	1,608	1,746
0.8	1,545	1,582	1,655	1,957
1	1,395	1,437	1,530	1,789
T(2/3)				
0.2	1,092	1,109	1,207	1,189
0.5	1,211	1,192	1,248	1,446
0.8	1,151	1,199	1,179	1,341
1	1,007	938	988	1,022
T(3/5)				
0.2	1,133	1,137		1,204
0.5	1,082	1,076	1,139	1,230
0.8	968	995	1,039	1,171
1	807	815	802	850

Time Period2	31-40			
Mean Starting HarvestRate	0.6	Mean Starting SSB		
				1,018
Promedio de Mean SSB2	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	1,043	1,078	984	1,122
0.5	1,166	1,159	1,238	1,184
0.8	1,161	1,184	1,102	1,227
1	962	915	904	680
T(1/2)				
0.2	1,484	1,426	1,444	1,516
0.5	1,827	1,762	1,855	2,038
0.8	1,787	1,909	2,045	2,379
1	1,675	1,635	1,788	2,125
T(1/3)				
0.2	1,449	1,470	1,568	1,631
0.5	1,766	1,896	1,953	2,172
0.8	1,821	1,868	2,021	2,446
1	1,595	1,683	1,845	2,231
T(2/3)				
0.2	1,194	1,201	1,312	1,340
0.5	1,320	1,304	1,400	1,720
0.8	1,298	1,312	1,351	1,611
1	1,032	973	1,042	1,092
T(3/5)				
0.2	1,190	1,205		1,310
0.5	1,135	1,117	1,204	1,357
0.8	969	981	1,125	1,297
1	686	724	682	779

Table 2. Mean TAC in the 20 and last ten years of the management period, according to the ratios of Observation Error over IAV (Columns) and by Harvest Control Rules and Uncertainty Cup levels (Rows), for two cases of harvest rates on the initial (starting) population prior to management: for the healthy starting population (Upper tables) and for the highly exploited starting population (Bottom tables). Uncertainty Cup of 1 means that there is no Uncertainty Cup constraint. MeanStHR means that the Starting mean Harvest Rate is taken a constant F_{proxy} for the future management of the population.

Time Period	21-40	Entire Management Period		
Mean Starting Harvest Rate	0.3	Mean starting TAC		
				601
Suma de Mean TAC	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	529	538	524	517
0.5	549	540	538	499
0.8	562	563	556	523
1	582	583	584	642
T(1/2)				
0.2	452	445	417	392
0.5	406	365	306	222
0.8	434	400	332	178
1	487	465	431	277
T(1/3)				
0.2	428	423	413	361
0.5	396	361	326	218
0.8	424	386	314	160
1	467	431	383	236
T(2/3)				
0.2	463	459	451	423
0.5	491	432	426	337
0.8	493	468	424	288
1	536	522	493	456
T(3/5)				
0.2	490	450	470	434
0.5	472	453	428	366
0.8	479	453	447	343
1	499	526	491	540

Time Period2	31-40	Last Ten years		
Mean Starting HarvestRate	0.3	Mean starting TAC		
				585
Suma de Mean TAC2	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	530	531	516	514
0.5	551	537	540	483
0.8	562	566	552	522
1	583	585	573	615
T(1/2)				
0.2	392	380	350	308
0.5	337	288	217	112
0.8	371	324	232	58
1	448	419	355	143
T(1/3)				
0.2	360	361	358	273
0.5	323	282	222	106
0.8	354	301	214	46
1	423	372	303	100
T(2/3)				
0.2	417	407	378	342
0.5	425	364	342	222
0.8	446	418	330	158
1	490	476	416	305
T(3/5)				
0.2	420	382	406	346
0.5	392	358	342	235
0.8	380	335	300	175
1	397	424	354	315

Time Period	21-40			
Mean Starting HarvestRate	0.6	Mean starting Catch		
				783
Suma de Mean TAC	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	501	539	494	471
0.5	542	584	592	507
0.8	604	586	547	506
1	566	558	538	567
T(1/2)				
0.2	363	340	319	285
0.5	413	353	323	205
0.8	444	389	326	173
1	498	456	420	285
T(1/3)				
0.2	350	330	348	294
0.5	405	358	317	207
0.8	432	389	347	162
1	479	475	411	246
T(2/3)				
0.2	358	362	379	315
0.5	443	400	395	273
0.8	458	451	409	289
1	522	452	470	452
T(3/5)				
0.2	414	372		354
0.5	433	430	423	358
0.8	445	438	425	358
1	557	500	514	572

Time Period2	31-40			
Mean Starting HarvestRate	0.6	Mean starting Catch		
				625
Suma de Mean TAC2	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	495	536	485	474
0.5	581	609	618	525
0.8	623	623	561	546
1	558	544	551	496
T(1/2)				
0.2	297	258	240	189
0.5	387	306	252	104
0.8	422	369	272	71
1	520	483	396	189
T(1/3)				
0.2	286	273	273	206
0.5	370	319	269	114
0.8	429	376	308	75
1	478	468	384	152
T(2/3)				
0.2	296	284	303	225
0.5	426	358	355	184
0.8	444	429	377	190
1	488	424	431	323
T(3/5)				
0.2	359	326		266
0.5	361	376	365	253
0.8	344	378	343	254
1	446	352	403	348

Table 3. Mean harvest rates in the 20 and last ten years of the management period (left and right tables), according to the ratios of Observation Error over IAV (Columns) and by Harvest Control Rules and Uncertainty Cup levels (Rows), for two cases of harvest rates on the initial (starting) population prior to management: for the healthy starting population (Upper tables) and for the highly exploited starting population (Bottom tables). Uncertainty Cup of 1 means that there is no Uncertainty Cap constraint. MeanStHR means that the Starting mean Harvest Rate is taken a constant F_{proxy} for the future management of the population.

Time Period	21-40	Entire Management Period		
Mean Starting HarvestRate	0.3	Mean Starting Hr		
				0.30
Promedio de Hr_SSB	ObsError			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	0.31	0.31	8183.76	6882.54
0.5	0.30	0.30	0.30	0.31
0.8	0.30	0.30	0.30	0.30
1	0.31	0.32	0.33	0.44
T(1/2)				
0.2	37144.51	40412.34	52833.97	70195.95
0.5	0.21	0.20	0.17	1821.37
0.8	0.22	0.21	1.33	0.72
1	0.25	0.24	0.22	0.17
T(1/3)				
0.2	48194.25	75318.49	20830.03	209880.38
0.5	0.20	11.93	3.25	11727.61
0.8	0.21	0.20	0.16	0.09
1	0.24	0.22	0.21	0.17
T(2/3)				
0.2	36167.65	55208.61	15128.02	53280.52
0.5	947.17	31.87	4950.31	351.23
0.8	6.36	8.57	41.27	187.52
1	12.19	14.16	22.64	223.11
T(3/5)				
0.2	23242.76	30668.98	69803.86	79032.99
0.5	14860.65	10082.13	3084.09	14525.82
0.8	2583.65	3003.73	6065.55	1610.13
1	1084.76	260.04	204.58	3611.84

Time Period2	31-40	Last Ten years		
Mean Starting HarvestRate	0.3	Mean Starting Hr		
				0.30
Promedio de Hr_SSB2	ObsError/			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	0	0.31	16261.70	13764.75
0.5	0.30	0.30	0.30	0.30
0.8	0.30	0.30	0.30	0.29
1	0.30	0.31	0.32	0.44
T(1/2)				
0.2	39214.91	73831.02	91597.46	134216.73
0.5	0.16	0.14	0.11	52.28
0.8	0.18	0.16	0.11	0.03
1	0.22	0.21	0.17	0.07
T(1/3)				
0.2	51048.86	130636.66	41646.22	147245.44
0.5	0.15	0.13	6.26	586.65
0.8	0.17	0.14	0.10	0.02
1	0.20	0.18	0.14	0.05
T(2/3)				
0.2	4270.62	17534.21	6179.66	84661.24
0.5	1365.98	7.26	273.26	193.29
0.8	7.38	16.63	59.97	104.87
1	19.13	9.06	19.55	22.90
T(3/5)				
0.2	39192.60	22842.73	81428.49	118204.64
0.5	8502.32	5963.24	2856.24	1889.30
0.8	4588.46	1412.50	1909.46	1863.33
1	2050.49	192.12	210.00	3171.45

Time Period	21-40			
Mean Starting Harvest	0.6			
Promedio de Hr_SSB	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	337016.53	235809.00	221653.26	259814.85
0.5	8.37	3108.30	2448.25	14443.68
0.8	3.96	2.67	0.59	15.00
1	0.62	0.66	0.73	1.31
T(1/2)				
0.2	292100.30	237762.67	263870.35	328177.17
0.5	151.10	1792.32	22141.86	16036.39
0.8	2.71	1.78	1.79	5.42
1	0.41	0.42	0.37	0.34
T(1/3)				
0.2	513245.08	174956.07	557552.51	377074.13
0.5	7141.00	25.43	698.64	3306.45
0.8	2.70	1.20	2.36	12.44
1	0.42	0.41	0.39	0.28
T(2/3)				
0.2	475578.18	356887.82	638655.31	262188.00
0.5	4587.12	37869.96	20825.12	33628.56
0.8	1208.84	852.36	374.17	846.10
1	89.84	853.50	151.08	6242.04
T(3/5)				
0.2	309670.56	572931.26		290561.20
0.5	118325.53	46205.06	130454.21	96874.90
0.8	9772.86	3541.25	10840.80	3859.10
1	11285.32	5826.30	9400.54	1657.83

Time Period 2	31-40			
Mean Starting Harvest	0.6			
Promedio de Hr_SSB2	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	633862.80	360405.97	310501.68	442448.59
0.5	0.56	9.97	2.69	28524.60
0.8	0.58	0.58	0.57	15.25
1	0.62	0.66	0.74	1.38
T(1/2)				
0.2	372932.80	349590.40	452337.26	272207.93
0.5	0.48	209.27	113.93	594.49
0.8	0.27	0.22	0.16	0.04
1	0.34	0.34	0.26	0.12
T(1/3)				
0.2	828565.96	188414.76	899193.39	145657.89
0.5	2900.70	3.24	558.29	425.15
0.8	0.26	0.24	0.18	8.79
1	0.34	0.33	0.26	0.09
T(2/3)				
0.2	717666.70	457526.33	623488.78	269910.81
0.5	1485.74	1386.81	2063.83	12018.14
0.8	526.73	410.31	161.25	790.68
1	71.79	74.38	102.03	159.07
T(3/5)				
0.2	450917.79	604601.11		330774.45
0.5	90085.61	41681.74	168945.53	99283.93
0.8	17351.02	2853.78	2933.69	5080.30
1	15373.27	665.31	5088.53	1163.02

Table 4. Probability of exceeding past Harvest rates on the Survey population during the last ten years of the management period compared to the maximum Hr values for the initial 20 years of unmanaged population, for the initial lightly (left) and heavily (right) exploited populations.

Time Period2	31-40	Last Ten years		
Mean Starting HarvestRate	0.3			
Suma de Prob(AboveMaxHrSPopY)	**ObsError/IAV**			
HCR & UnCup	**0.50**	**0.70**	**1.00**	**2.00**
MeanStHR				
0.2	0	0.09	0.11	0.17
0.5	0.02	0.03	0.08	0.13
0.8	0.01	0.04	0.08	0.15
1	0.02	0.07	0.15	0.29
T(1/2)				
0.2	0.14	0.13	0.15	0.15
0.5	0.05	0.05	0.04	0.05
0.8	0.05	0.04	0.04	0.05
1	0.05	0.07	0.07	0.08
T(1/3)				
0.2	0.11	0.11	0.11	0.12
0.5	0.03	0.05	0.05	0.05
0.8	0.05	0.06	0.05	0.04
1	0.07	0.07	0.08	0.07
T(2/3)				
0.2	0.18	0.18	0.22	0.20
0.5	0.15	0.13	0.16	0.13
0.8	0.17	0.15	0.14	0.12
1	0.20	0.20	0.18	0.17
T(3/5)				
0.2	0.26	0.23	0.25	0.24
0.5	0.24	0.24	0.22	0.23
0.8	0.25	0.27	0.24	0.20
1	0.23	0.25	0.24	0.26

Time Period2	31-40			
Mean Starting HarvestRate	0.6			
Suma de Prob(AboveMaxHrSPopY)2	**ObsEr**			
HCR & UnCup	**0.50**	**0.70**	**1.00**	**2.00**
MeanStHR				
0.2	0	0.18	0.24	0.25
0.5	0.02	0.04	0.06	0.15
0.8	0.00	0.03	0.05	0.10
1	0.01	0.04	0.09	0.20
T(1/2)				
0.2	0.16	0.19	0.19	0.21
0.5	0.00	0.02	0.02	0.05
0.8	0.00	0.00	0.00	0.00
1	0.00	0.01	0.01	0.01
T(1/3)				
0.2	0.17	0.16	0.16	0.14
0.5	0.01	0.01	0.01	0.02
0.8	0.00	0.00	0.00	0.01
1	0.02	0.02	0.02	0.00
T(2/3)				
0.2	0.26	0.26	0.26	0.26
0.5	0.12	0.13	0.12	0.13
0.8	0.10	0.13	0.10	0.11
1	0.13	0.11	0.11	0.09
T(3/5)				
0.2	0.26	0.27		0.27
0.5	0.21	0.23	0.23	0.19
0.8	0.27	0.26	0.24	0.24
1	0.26	0.24	0.24	0.27

Table 5. Probability of falling below the minimum spawning biomass observed in the past during the last ten years of the management period compared to the minimum SSB values for the initial 20 years of unmanaged population, for the initial lightly (left) and heavily (right) exploited populations.

Time Period2	31-40	Last Ten years		
Mean Starting HarvestRate	0.3	Mean Starting Risk		
				0
Promedio de Prob(BelowMinSSB)2	ObsError			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	0	0.10	0.12	0.14
0.5	0.08	0.09	0.09	0.12
0.8	0.09	0.09	0.09	0.10
1	0.07	0.09	0.13	0.24
T(1/2)				
0.2	0.13	0.11	0.14	0.13
0.5	0.03	0.04	0.03	0.03
0.8	0.03	0.03	0.03	0.02
1	0.04	0.04	0.04	0.03
T(1/3)				
0.2	0.12	0.10	0.10	0.11
0.5	0.04	0.04	0.03	0.02
0.8	0.03	0.03	0.03	0.01
1	0.04	0.03	0.03	0.03
T(2/3)				
0.2	0.14	0.14	0.19	0.19
0.5	0.09	0.08	0.12	0.11
0.8	0.12	0.10	0.12	0.09
1	0.12	0.13	0.16	0.26
T(3/5)				
0.2	0.21	0.21	0.20	0.23
0.5	0.21	0.21	0.19	0.23
0.8	0.24	0.27	0.27	0.22
1	0.28	0.33	0.32	0.44

Time Period2	31-40			
Mean Starting HarvestRate	0.6	Mean Starting Risk		
				0
Promedio de Prob(BelowMinSSB)2	ObsError/IAV			
HCR & UnCup	0.50	0.70	1.00	2.00
MeanStHR				
0.2	0	0.26	0.32	0.29
0.5	0.11	0.12	0.12	0.19
0.8	0.10	0.09	0.13	0.13
1	0.20	0.21	0.21	0.38
T(1/2)				
0.2	0.24	0.27	0.27	0.30
0.5	0.03	0.07	0.09	0.10
0.8	0.02	0.02	0.01	0.02
1	0.02	0.04	0.02	0.03
T(1/3)				
0.2	0.27	0.23	0.26	0.23
0.5	0.06	0.03	0.04	0.06
0.8	0.01	0.01	0.02	0.02
1	0.02	0.02	0.02	0.01
T(2/3)				
0.2	0.35	0.34	0.33	0.36
0.5	0.17	0.20	0.18	0.20
0.8	0.15	0.15	0.15	0.18
1	0.18	0.23	0.25	0.31
T(3/5)				
0.2	0.32	0.35		0.35
0.5	0.31	0.31	0.30	0.30
0.8	0.34	0.37	0.34	0.34
1	0.49	0.46	0.50	0.54

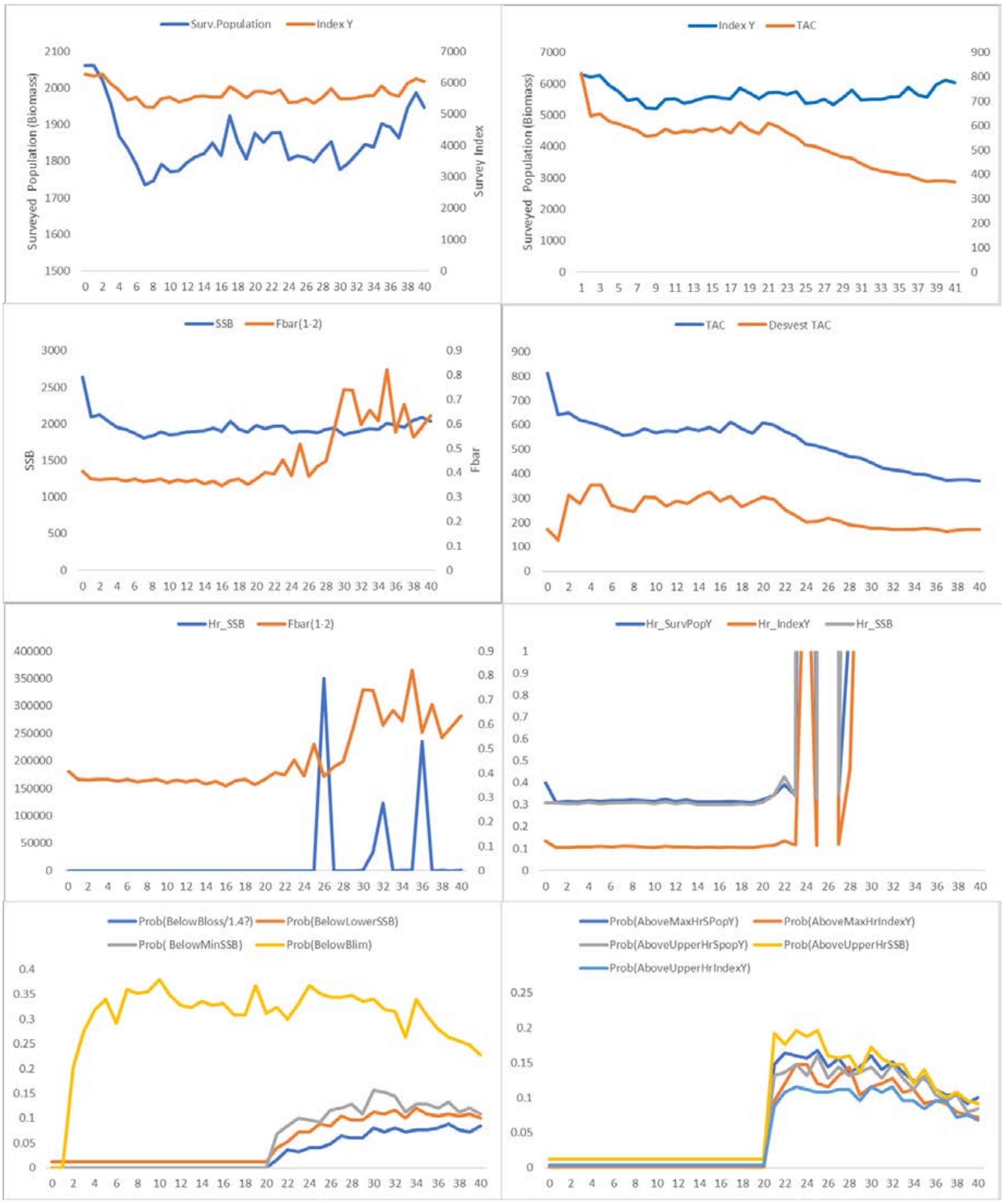

Figure 1. Mean behaviour of the T(1/2) with 20% UnCap for a starting population being sustainably harvested and observation error half (0.5) the IAV.

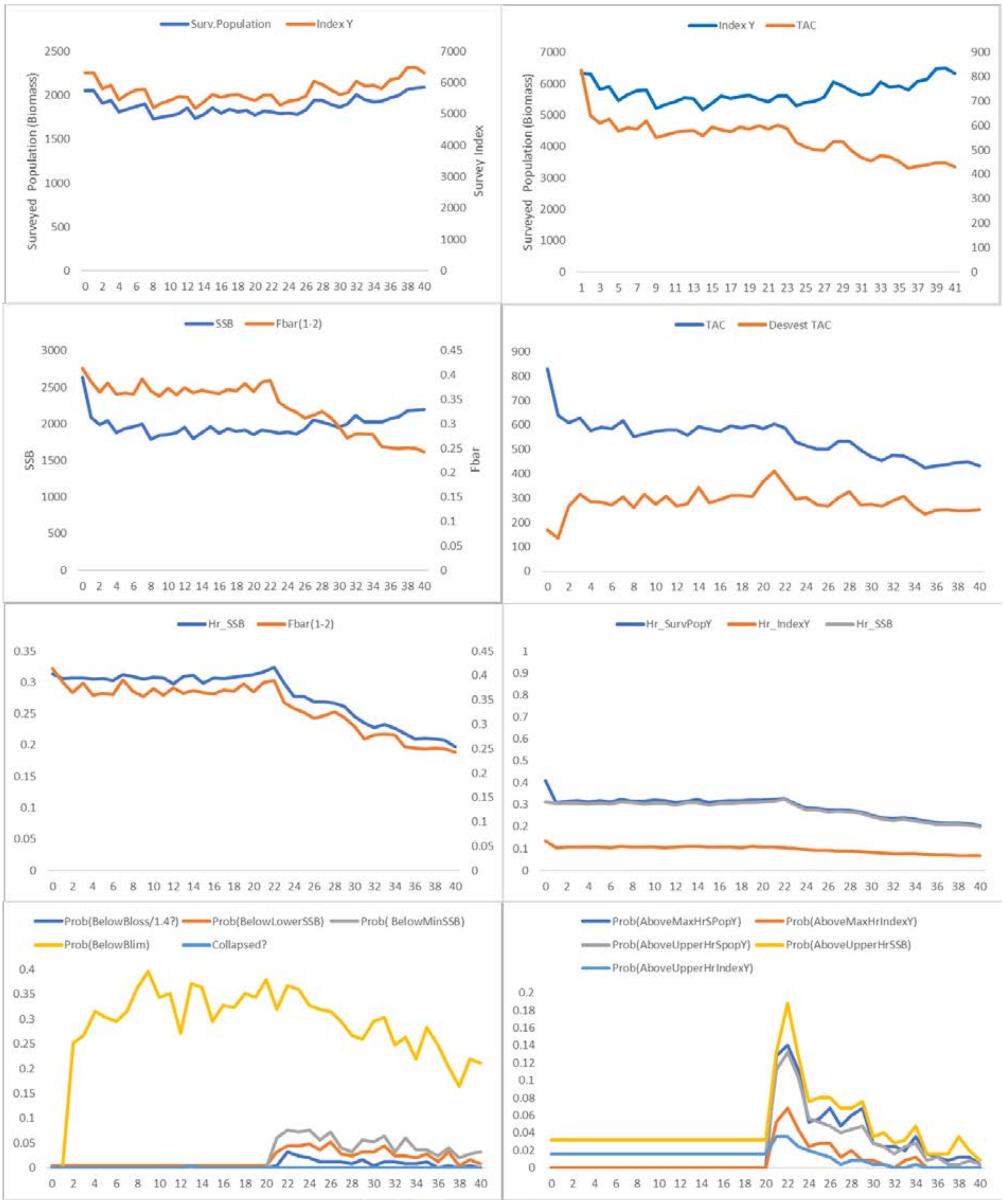

Figure 2. Mean behaviour of the T(1/2) with No UnCap for a starting population being sustainably harvested and for and observation error half (0.5) the IAV.

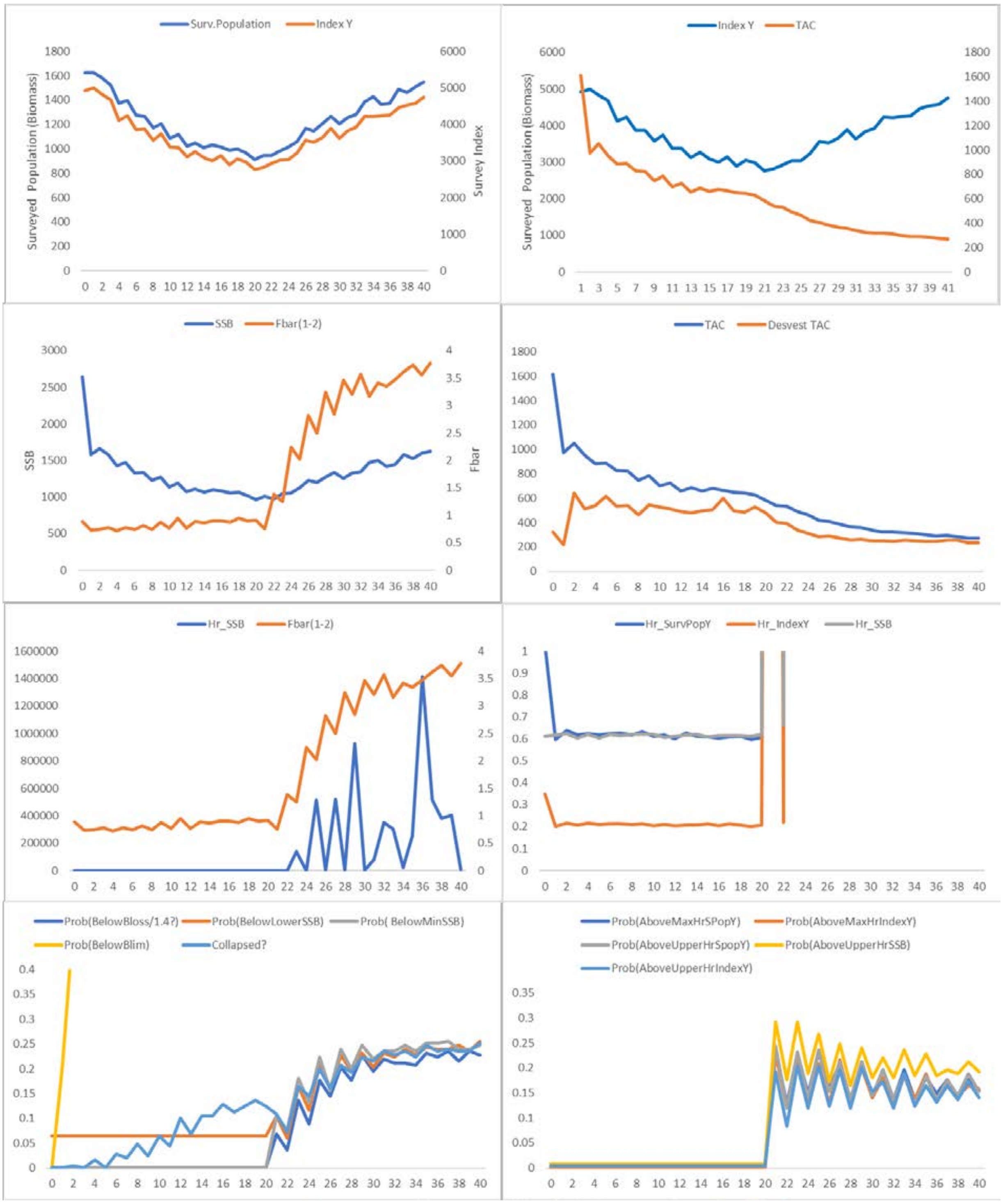

Figure 3. Mean behaviour of the T(1/2) with 20% UnCap for a starting population being harvested at a high harvest (around but below deterministic F_{MSY}) and for and observation error half the IAV (0.5).

Figure 4. Mean behaviour of the T(1/2) with No UnCap for a starting population being harvested at a high harvest (around but below deterministic F_{MSY}) and for and observation error half the IAV (0.5).

A3.4 Discussion

Probably, the major factors conditioning the performance of the survey trend-based management harvest rules for short-lived species could be:

a) The information content of the Indicator on the population being managed. This is related to the % of biomass being harvested and managed which is covered by the Survey index. This is related to the surveyed population (ages classes fully covered by the survey) and to the time gap between the availability of the indicator and the management decision, i.e. two surveys having the same coverage of the age classes of the population may result in different performance of parallel trend harvest rules if the such information is used for in-year management or if it used for managing the population of the next year.

b) The ratio of the interannual variability of the population (IAV) vs. the observation error of the indicator. So that the larger the IAV is compared with the observation error the more the advice can rely on the yearly trends suggested by the most recent indicator.

c) The knowledge of the F_{proxy} or sustainable harvest applicable to the stock index. Here we just assumed it was not known and assess the risk over the past statistics of the fishery and population time-series.

In this annex (Working Document), the authors have played with survey index informing on the actual recruitment-at-age 1 in the management year, which is the youngest age group contributing to the spawning stock. This supposes an advantage over the surveys not informing on the youngest age class to spawning (being this the managed population in terms of risks). This has been used for in-Year advice. This a major difference with the traditional application of the trend-based DLS methods: Major difference of In-Year advice, based on surveys compared with classical methods, is that the Index includes information on all age classes contributing to the managed population and SSB (at least for the first half of the management year).

The analysis shows that Rules T(1/2) and T(1/3), applied with no uncertainty cap or with 80% uncertainty cap, outperform other rules in terms of increasing biomasses while still allowing substantial catches (similar or higher to the ones produced with the other HCR). At the same time, they tend to avoid exceeding maximum past harvest rates. This was shown here for an initially highly exploited population (around deterministic F_{MSY}) and also for a moderate/high harvested starting population. This confirms the benefits of in-year advice being guided by the most recent information of trend in the populations as shown by HCRs T(1/2) and T(1/3), while other rules T(2/3) and T(3/5) encapsulate longer past trends which are probably not suitable for these fast fluctuating populations. The latter rules show the poorer recovery of the population to higher SSBs and lead to high risks of exceeding maximum past harvest rates and their performance worsen with the 20% cap constraint.

Regarding the Uncertainty Cap, 20% uncertainty cap led often to unrealistic mean harvest rates as results of occasional stock collapses even for T(/1/2) rule, meaning that such restriction in the year-to-year change of advisable catches can become in risky situations of too high allowable level of catches when drastic biomass reductions occur in these short-lived species. In practice, lowest risks of exceeding maximum past harvest rates and of falling below minimum past SSB (and of collapses) occur for the most flexible HCR (T(1/2) and T(1/3), for none or for 80% uncertainty cap constrained, which suggest that this is the only way to accommodate the advice to such fluctuating fish resources and of minimizing risky situations.

Globally, the higher the ratio of the observation error over the IAV the poorer is the performance of the rules in avoiding too high harvest rates, but this becomes noticeable particularly at a ratio of 2.

Finally, using the Mean past Harvest rate as an F_{proxy} for method 3.3) shows a good consistent result keeping the original harvest rate throughout the whole managed period with acceptable levels of risk of except for the cases of 20% uncertainty cap and/or of very high Observation Error (2), where the performance worsens and leads to some cases of stock collapse too and high risks of exceeding highest past Harvest rates.

Concluding remarks

- The ratio of Observation Error over the IAV conditions the performance of any HCR. The larger it is, the harder will be any management HCR. Testing of HCRs should account for both the IAV and the Observation error.
- The Uncertainty Cap worse the performance of the HCRs for this species with high IAV. Only uncertainty caps of 80% and no uncertainty cap allow good long-term behaviour of the rule, particularly for T(1/2) and T(1/3).
- Rule informing on the most recent changes in the population (T(1/2) or T(1/3)) seems to outperform the other rules T(2/3) and T(3/5) for in-year advice (as the latter rules imply tracking longer term changes and allowing larger delays between the trends and its application to the management).
- Best candidates for short lived species are T(1/2) or T(1/3) with no Uncertainty Cap followed closely with 80% of Uncertainty Cap. We think these results can be generalized to other short-lived species.
- The performance of fixed harvest rate approach (taken from the mean past Hr of the 20 years) will always depend on the sustainability of such F. It might be a good candidate, if properly estimated through a suitable historical assessment.
- The starting catch to provide the first advice on TAC for the management period, matters and more time and carefully analysis of the starting point is advisable (not worked here).

Pending issues

- Generalization to other stocks such as:
  - Sardine in 8.abd (simulations are run)
  - Bay of Biscay anchovy?
  - Sprat?
- Assessing the influence of the starting catch and proposing ways to select or estimate an appropriate one.
- Precautionary Buffer? (related to the above one)
- *Ad hoc* tactical modifications of the rules according to the results of their application?
  - As the one suggested in WKMSYCAT34? Such as a correction multiplier for the cases of surpassing lowest SSB values ($B_{triggers}$).

- Better understanding of the long-term performance of the rules (so far only 20 years ahead simulations have been tested).

Table 3.1. Conditioning the Anchovy in 9.a.

FISHERY AND BIOLOGICAL BASIC DATA DEFINITION

Definition of the Seasonal Fishery by the faction of catches in the first half of the year

Fraction Catches Sem 1 0.35

Starting Random Harvest Rate Model

Mean Starting HarvestRate Hr(SSB.Y+1)	**0.3**	
Log Sigma	**0.2**	Variability

FIRST HALF OF THE YEAR (July-December) **INPUTS**

Manag.Year 142 **First Half of the Year (July- December)**

Age	M at age	Mat	PF	PM	SWt	FishingPatte	CWt	Sel Relat Relative Selectivity
0	*1.1000*	0	0	0	0.0055	*0.262*	0.005468	0.2621
1	*0.6500*	1	0	0	0.0162	*0.876*	0.0162184	0.8758
2	*0.6500*	1	0	0	0.0234	*0.961*	0.0233508	0.9608
3	*0.6500*	1	0	0	0.0282	*1.000*	0.0281947	1.0000
4	*0.6500*	1	0	0	0.0282	*1.000*	0.0281947	1.0000
5	*0.6500*	1	0	0	0.0282	*1.000*	0.0281947	1.0000
6	*0.6500*	1	0	0	0.0282	*1.000*	0.0281947	1.0000

Mbar(2-5)	*0.6500*	F(1-2)	0.9183
Mbar(1-5)	*0.6500*	Apical F	1.000

Process Error in M

LogProcessError	**0.000**	Annual Sigma in M

SECOND HALF OF THE YEAR (January-June) **INPUTS**

From First Sem **Second Half of the Year (January- June)**

Age	Mean M (a	Catchability	PF_Surv	PM_Surv	SWt	FishingPattern	CWt	Sel Relat Relative Selectivity
0	1.100	0	0.75	0.75	0.0055	0.0000	0.0055	0.0000
1	0.650	0.7	0.75	0.75	0.0162	0.8758	0.0162	0.8758
2	0.650	1	0.75	0.75	0.0234	0.9608	0.0234	0.9608
3	0.650	1	0.75	0.75	0.0282	1.0000	0.0282	1.0000
4	0.650	1	0.75	0.75	0.0282	1.0000	0.0282	1.0000
5	0.650	1	0.75	0.75	0.0282	1.0000	0.0282	1.0000
6	0.650	1	0.75	0.75	0.0282	1.0000	0.0282	1.0000

F(1-2)	0.9183
Apical F	1.000

OBSERVATION MODELLING OF THE SURVEY INDEX

Observation Error from Surv. Or Assessment

Mean Catchability	**3**	
Log Sigma	**0.358**	Standard Deviation in log Scale (LN)

Catchability by age and PF and PM_Surv on half year basis are shown to the left

CV Natural Cooresponding to LogSigma

Initial Unexploited Population

Age	Month1Sem2 January	Month1Sem1 July	
0	1,783,238	593,588	595,973
1	198,382	103,565	103,835
2	54,207	28,298	28,469
3	14,862	7,759	7,843
4	4,094	2,137	2,131
5	1,112	581	585
6	422	220	222
	SSB.january	SSB.July	
	5,061	2,642	

IAV
0.347

FishingPattern
0.2621
0.8758
0.9608
1.0000
1.0000
1.0000
1.0000
1.0000

RECRUITMENT MODELLING

Basic Information

Historial de R		**BRP**	Blim	1440	
R 1989-2017			MSY Btrigger	2361.6	=Bpa=Bloss Blo:
1,794,941	thousands mean 1989-2016				
1,632,485	thousands geo mean 1989-2016	**Next Recruitment (Hockey stick)**			
3,397,185	Max Rec 1989-2016 thousands		**Inflection Point**	**1440**	=Blim
			Slope	1.13367	
Log Sigma			Normal_R	1,632	Geometric Mean
0.471	hasta 2016				
			Log Sigma	0.471	

Table 3.2. Extract.

	Anchovy Like Stock	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL
	IAV	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36
	LogStdvObserv	0.179	0.179	0.179	0.179	0.358	0.358	0.358	0.358	0.716	0.716	0.716	0.716	0.250	0.250	0.250	0.250
	Ratio Stdv(Obs)/IAV	**0.50**	**0.50**	**0.50**	**0.50**	**1.00**	**1.00**	**1.00**	**1.00**	**2.00**	**2.00**	**2.00**	**2.00**	**0.70**	**0.70**	**0.70**	**0.70**
	Mbar(1-5)	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3
	LogStdvM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	LogStdRec	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47
	InflectionPoint (Blim)	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440
	Mean Starting HarvestRate	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**	**0.3**
	LogStdHr	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
	HCR	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)
	HCRNume#	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	HCRDeno#	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	HCRCatch#	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	UnCap	**0.2**	**0.5**	**0.8**	**1**	**0.2**	**0.5**	**0.8**	**1**	**0.2**	**0.5**	**0.8**	**1**	**0.2**	**0.5**	**0.8**	**1**
0-20	**Time Period**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**
601	Mean TAC	452	406	434	487	417	306	332	431	392	222	178	277	445	365	400	465
280	Desvest(TAC)	193	218	242	284	210	189	243	313	203	190	199	416	195	216	243	315
1,965	Mean SSB	1,946	2,095	2,069	2,015	1,968	2,145	2,201	2,083	2,003	2,254	2,330	2,202	1,991	2,124	2,096	2,023
0.37	Surv.Population	1,857	1,996	1,972	1,919	1,878	2,041	2,095	1,983	1,909	2,144	2,216	2,093	1,898	2,022	1,995	1,927
0.31	Index Y	5,652	6,105	5,981	5,861	5,937	6,521	6,722	6,283	7,293	8,374	8,499	8,223	5,868	6,263	6,175	5,979
0.32	Fbar(1-2)	0.56	0.25	0.26	0.30	0.78	0.19	0.21	0.26	1.07	0.27	0.13	0.22	0.87	0.23	0.24	0.29
0.11	**Hr_SSB**	37,144.51	0.21	0.22	0.25	52,833.97	0.17	1.33	0.22	70,195.95	1,821.37	0.72	0.17	40,412.34	0.20	0.21	0.24
0.00	Hr_SurvPopY	3,951.66	0.22	0.23	0.26	4,513.16	0.17	0.33	0.23	6,351.91	233.83	0.22	0.15	4,863.44	0.20	0.21	0.25
0.01	Hr_IndexY	1,341.44	0.07	0.08	0.08	1,462.24	0.06	0.14	0.07	1,344.70	16.55	0.09	0.04	1,969.01	0.07	0.07	0.08
0.00	Prob(BelowMinSSB)	0.12	0.05	0.05	0.05	0.13	0.05	0.05	0.06	0.12	0.05	0.05	0.07	0.11	0.06	0.05	0.06
0.29	Prob(BelowLowerSSB)	0.09	0.03	0.03	0.03	0.11	0.04	0.03	0.04	0.11	0.04	0.04	0.05	0.10	0.05	0.03	0.04
0.00	Prob(BelowBloss/1.4?)	0.06	0.01	0.01	0.01	0.08	0.01	0.01	0.02	0.08	0.03	0.02	0.03	0.06	0.02	0.01	0.02
0.03	Prob(BelowBlim)	0.31	0.24	0.24	0.28	0.30	0.21	0.19	0.25	0.28	0.19	0.16	0.21	0.28	0.23	0.23	0.27
0.01	Prob(AboveMaxSSB)	0.06	0.06	0.07	0.06	0.07	0.09	0.08	0.07	0.08	0.11	0.11	0.09	0.08	0.08	0.07	0.07
0.00	Prob(AboveUpperSSB)	0.04	0.04	0.04	0.04	0.04	0.06	0.05	0.04	0.05	0.06	0.07	0.06	0.05	0.05	0.04	0.04
0.01	Prob(AboveUpperHrSSB)	0.15	0.06	0.05	0.06	0.16	0.04	0.05	0.08	0.16	0.06	0.05	0.08	0.14	0.05	0.05	0.08
0.00	Prob(AboveMaxHrSPopY)	0.14	0.05	0.05	0.05	0.15	0.04	0.04	0.07	0.15	0.05	0.05	0.08	0.13	0.05	0.04	0.07
0.00	Prob(AboveUpperHrSpopY)	0.13	0.04	0.04	0.04	0.14	0.03	0.04	0.06	0.14	0.05	0.04	0.08	0.12	0.04	0.04	0.06
0.00	Prob(BelowMinHrSPopY)	0.38	0.56	0.52	0.38	0.48	0.72	0.70	0.56	0.52	0.80	0.87	0.79	0.42	0.64	0.57	0.48
0.00	Prob(AboveMaxHrIndexY)	0.11	0.03	0.01	0.02	0.10	0.01	0.01	0.01	0.06	0.01	0.00	0.00	0.09	0.01	0.01	0.02
1.08	Prob(AboveUpperHrIndexY)	0.10	0.02	0.01	0.01	0.08	0.00	0.00	0.00	0.06	0.01	0.00	0.00	0.08	0.01	0.00	0.01
1.02	Prob(BelowMinHrIndexY)	0.30	0.47	0.41	0.27	0.29	0.54	0.53	0.32	0.17	0.54	0.68	0.56	0.30	0.52	0.43	0.33
1.02	TrendSSB?	1%	8%	6%	5%	0%	12%	13%	7%	4%	19%	21%	13%	3%	8%	9%	5%
1.04	TrendHr(SSB)?	11971993%	-30%	-27%	-19%	17128679%	-46%	352%	-27%	22840253%	536325%	127%	-45%	13461227%	-37%	-32%	-21%
1-10	TrendHr(SPopY)?	1209538%	-31%	-29%	-21%	1390600%	-47%	4%	-29%	1958982%	65508%	-32%	-51%	1544356%	-38%	-33%	-22%
585	TrendHR(IndexY)?	1195108%	-33%	-30%	-23%	1331563%	-51%	20%	-37%	874582%	10399%	-34%	-70%	1918394%	-41%	-37%	-28%
292	**Time Period**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**
1,923	Mean TAC	392	337	371	448	350	217	232	355	308	112	58	143	380	288	324	419
0.36	Desvest(TAC)	171	189	215	261	194	149	183	257	172	125	86	243	171	188	212	290
0.30	Mean SSB	1,977	2,235	2,169	2,093	1,994	2,308	2,338	2,189	2,040	2,448	2,518	2,407	2,019	2,281	2,213	2,132
0.32	Surv.Population	1,884	2,127	2,065	1,992	1,900	2,195	2,225	2,081	1,943	2,327	2,396	2,289	1,923	2,170	2,107	2,030
0.11	Index Y	5,744	6,508	6,268	6,090	5,981	7,047	7,112	6,598	7,550	9,099	9,296	8,981	5,950	6,732	6,527	6,275
0.00	Fbar(1-2)	0.64	0.19	0.21	0.26	0.97	0.12	0.13	0.20	1.43	0.19	0.03	0.08	1.14	0.17	0.19	0.25
0.01	**Hr_SSB**	39,214.91	0.16	0.18	0.22	91,597.46	0.11	0.11	0.17	134,216.73	52.28	0.03	0.07	73,831.02	0.14	0.16	0.21

Table 3.3. Extract.

	Anchovy Like Stock	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL
	IAV	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36
	LogStdvObserv	0.179	0.179	0.179	0.179	0.358	0.358	0.358	0.358	0.716	0.716	0.716	0.716	0.250	0.250	0.250	0.250
	Ratio Stdv(Obs)/IAV	**0.50**	**0.50**	**0.50**	**0.50**	**1.00**	**1.00**	**1.00**	**1.00**	**2.00**	**2.00**	**2.00**	**2.00**	**0.70**	**0.70**	**0.70**	**0.70**
	Mbar(1-5)	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3
	LogStdvM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	LogStdRec	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47
	InflectionPoint (Blim)	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440
	Mean Starting HarvestRate	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**
	LogStdHr	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
	HCR	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)	T(1/2)
	HCRNume#	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	HCRDeno#	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	HCRCatch#	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	UnCap	**0.2**	**0.5**	**0.8**	**1**	**0.2**	**0.5**	**0.8**	**1**	**0.2**	**0.5**	**0.8**	**1**	**0.2**	**0.5**	**0.8**	**1**
0-20	**Time Period**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**	**21-40**
783	Mean TAC	363	413	444	498	319	323	326	420	285	205	173	285	340	353	389	456
483	Desvest(TAC)	276	277	321	371	266	260	286	383	242	205	220	517	273	263	283	393
1,279	Mean SSB	1,318	1,547	1,526	1,450	1,273	1,530	1,691	1,509	1,340	1,660	1,916	1,685	1,274	1,479	1,607	1,377
1,181	Surv.Population	1,253	1,470	1,450	1,379	1,211	1,453	1,604	1,433	1,275	1,574	1,815	1,595	1,213	1,405	1,525	1,308
3,645	Index Y	3,817	4,476	4,406	4,199	3,863	4,668	5,113	4,518	4,954	6,159	7,066	6,097	3,771	4,316	4,728	4,046
0.80	Fbar(1-2)	2.87	0.41	0.39	0.45	3.53	0.58	0.29	0.41	3.64	1.40	0.20	0.35	3.57	0.68	0.34	0.45
0.61	**Hr_SSB**	292,100.30	151.10	2.71	0.41	263,870.35	22,141.86	1.79	0.37	328,177.17	16,036.39	5.42	0.34	237,762.67	1,792.32	1.78	0.42
0.64	Hr_SurvPopY	28,627.53	18.55	0.60	0.40	24,698.28	1,932.26	0.47	0.35	30,683.59	1,358.70	0.93	0.25	22,382.39	175.53	0.46	0.40
0.22	Hr_IndexY	10,326.70	7.33	0.19	0.13	9,027.95	600.71	0.18	0.11	11,873.23	729.39	0.41	0.07	8,006.28	61.35	0.14	0.13
0.00	Prob(BelowMinSSB)	0.21	0.05	0.05	0.05	0.23	0.12	0.03	0.05	0.26	0.12	0.05	0.08	0.23	0.09	0.04	0.07
0.09	Prob(BelowLowerSSB)	0.20	0.05	0.04	0.03	0.22	0.10	0.03	0.04	0.25	0.12	0.04	0.07	0.23	0.08	0.03	0.05
0.00	Prob(BelowBloss/1.4?)	0.18	0.03	0.02	0.02	0.20	0.08	0.01	0.02	0.23	0.10	0.03	0.05	0.21	0.06	0.02	0.03
0.64	Prob(BelowBlim)	0.58	0.51	0.52	0.57	0.59	0.51	0.44	0.53	0.57	0.45	0.36	0.45	0.60	0.54	0.49	0.60
0.00	Prob(AboveMaxSSB)	0.07	0.08	0.07	0.06	0.08	0.10	0.09	0.07	0.09	0.11	0.15	0.10	0.07	0.08	0.09	0.05
0.01	Prob(AboveUpperSSB)	0.03	0.03	0.02	0.02	0.03	0.03	0.04	0.02	0.05	0.05	0.08	0.04	0.03	0.03	0.04	0.02
0.02	Prob(AboveUpperHrSSB)	0.21	0.05	0.04	0.05	0.25	0.07	0.04	0.06	0.25	0.11	0.04	0.07	0.25	0.07	0.03	0.07
0.00	Prob(AboveMaxHrSPopY)	0.17	0.03	0.03	0.02	0.21	0.05	0.02	0.04	0.21	0.09	0.03	0.05	0.20	0.04	0.02	0.03
0.01	Prob(AboveUpperHrSpopY)	0.17	0.03	0.02	0.02	0.20	0.05	0.02	0.03	0.21	0.09	0.03	0.05	0.20	0.04	0.02	0.03
0.00	Prob(BelowMinHrSPopY)	0.52	0.62	0.61	0.49	0.53	0.68	0.77	0.62	0.56	0.76	0.87	0.80	0.52	0.66	0.69	0.52
0.00	Prob(AboveMaxHrIndexY)	0.17	0.02	0.01	0.01	0.17	0.03	0.01	0.01	0.15	0.05	0.00	0.00	0.17	0.03	0.01	0.01
0.01	Prob(AboveUpperHrIndexY)	0.16	0.02	0.01	0.01	0.17	0.03	0.01	0.00	0.14	0.05	0.00	0.00	0.17	0.03	0.00	0.01
0.00	Prob(BelowMinHrIndexY)	0.47	0.55	0.55	0.43	0.42	0.55	0.65	0.46	0.32	0.57	0.72	0.60	0.45	0.57	0.58	0.40
1.32	TrendSSB?	9%	26%	27%	21%	9%	28%	36%	25%	17%	36%	53%	35%	11%	21%	36%	17%
1.02	TrendHr(SSB)?	47299257%	25500%	314%	-33%	43864615%	3585049%	180%	-40%	54353949%	2752108%	781%	-44%	38650973%	299376%	191%	-32%
1.04	TrendHr(SPopY)?	4557888%	2891%	-7%	-37%	3949781%	298711%	-27%	-45%	4895710%	218817%	45%	-60%	3497859%	27982%	-27%	-37%
1.07	TrendHR(IndexY)?	4809312%	3433%	-14%	-39%	4177578%	269643%	-23%	-51%	4512398%	295848%	51%	-75%	3744219%	28737%	-33%	-41%
1-10	**Time Period**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**	**31-40**
625	Mean TAC	297	387	422	520	240	252	272	396	189	104	71	189	258	306	369	483
484	Desvest(TAC)	247	251	279	361	218	202	220	334	189	114	108	348	228	215	264	393
1,018	Mean SSB	1,484	1,827	1,787	1,675	1,444	1,855	2,045	1,788	1,516	2,038	2,379	2,125	1,426	1,762	1,909	1,635
966	Surv.Population	1,411	1,739	1,700	1,595	1,376	1,761	1,943	1,700	1,442	1,934	2,258	2,014	1,358	1,673	1,815	1,555
2,981	Index Y	4,302	5,292	5,162	4,854	4,457	5,692	6,221	5,364	5,550	7,546	8,739	7,690	4,223	5,143	5,608	4,839
0.83	Fbar(1-2)	3.49	0.29	0.31	0.40	4.29	0.44	0.18	0.30	4.42	1.37	0.05	0.14	4.56	0.58	0.26	0.39
0.62	**Hr_SSB**	372,932.80	0.48	0.27	0.34	452,337.26	113.93	0.16	0.26	272,207.93	594.49	0.04	0.12	349,590.40	209.27	0.22	0.34

Annex 4: Workshop agenda

IPMA, Lisbon, 8–12 October 2018

Agenda

Daily schedule (except 8 October: Start at 09:30 and 12 October: Finish at 13:00 *provisional*):

09:00	start
11:00	Coffee-break
13:00	Lunch
16:00	Coffee-break
18:00	end

08 October

09:30–10:00

- General meeting set up, accessing WiFi, meeting facility orientation, introductions & meeting ToRs.
- Expectations of reviewers.

10:00–13:00

- Presentation & plenary discussion:

  Simon – 'MSE testing of catch rules in FLR'

  Tanja – 'Testing length-based indicators for management of elasmobranchs'

14:00–18:00

- Presentation & plenary discussion:

  Tobias – 'SPiCT and MSE testing of catch rules'

  Laurie – 'MYDAS project'

09 October

09:00–17:00

- Subgroups work.
- Presentation & plenary discussion:

  Mark – 'Probyfish & testing of indicators'

  Andres – 'Testing the performance of different catch rules based on survey trends for the management of short-lived category 3 stocks'

  Alfonso – 'DLS for dome shaped selectivity. MSE testing with DLMtool'

- Subgroups work.

10 October

09:00–13:00

- Subgroups work.

14:00–18:00

- Plenary session: subgroup work progress and discussion.
- Report template.
- Subgroups work.

20:00 WKLIFE participants' dinner.

11 October

09:00–18:00

- Plenary sessions: subgroup work progress and discussions
- Subgroups work.
- Report writing and collation.

12 October

09:00–15:00

- Plenary session: conclusions & report adoption.

Annex 5: WKLIFE VIII List of participants

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Annex 6: External reviewers' report

External Reviewers

Chantel Wetzel – National Oceanic and Atmospheric Administration, USA

Adrian Hordyk – University of British Columbia, Canada

Introduction

The two external reviewers participated in the workshop discussions and provided advice and suggestions for additional analyses that were carried out and presented throughout the week. They also reviewed the draft workshop report and provided feedback on summarizing the conclusions in the report.

The reviewers were satisfied that the workshop addressed the terms of reference, and in general support the approach and conclusions of the workshop and report.

In this report, the reviewers' first present brief comments on the main scientific work presented at the workshop and then provide general recommendations for future research.

WKLIFE VIII Workshop and Report

1. MSE testing of advice rules based on surplus productions models

This work addressed Terms of Reference (a-i) – testing the SPiCT model and advice rules within an MSE framework, and (b) – evaluate the advice rules for short-lived species. Three classes of advice rules were tested within the DLMtool MSE framework with operating models based on 6 stocks (anchovy, pilchard, haddock, pollack, ling, and megrim) covering the range of life-history types in ICES category 3 & 4 stocks.

Discussions of the initial results lead to several further analyses that were explored throughout the workshop:

1) Recruitment variability of the initial simulations was very low, which may result in an overly optimistic evaluation of the assessment method and advice rule. Further simulations were recommended with increasingly high levels of recruitment process error to determine the influence of this parameter of the performance of the SPiCT model and advice rules.

2) The B_{lim} and $B_{trigger}$ reference points in the initial simulations were not consistent with the usual ICES practice and were corrected in the further simulations.

3) The operating model for Scenario 6 was revised so that the fishery still had a long exploitation history, but only data from the most recent years were available to the SPiCT assessment.

4) The dt_{euler} parameter specifies the temporal resolution of the SPiCT model. For purposes of speed, the initial analyses were run with a dt_{euler} value of 1. Further analyses were conducted with smaller values of dt_{euler} to evaluate the trade-offs in model run time, convergence rate, and performance in closed-loop simulation.

5) Convergence diagnostics were recommended to determine if sufficient simulations had been run to produce stable results, and to identify the simulations where the SPiCT model often failed to converge.

6) By default, the SPiCT model estimates the shape parameter (n) in the Pella-Tomlinson production model. However, this parameter is notoriously difficult to estimate, particularly when there is little contrast in the index of population abundance. Simulations were run to evaluate the consequences of fixing a tight prior for the n parameter. Preliminarily results suggest that fixing the shape parameter resulted in better convergence and more precise estimates of the SPiCT model. Further research is required to evaluate the trade-offs in performance of the SPiCT model under these conditions in closed-loop simulation.

Due to time constraints during the meeting, each of the reviewers requested further explorations were focused on a subset of the simulated stocks (anchovy, haddock, and ling).

The MSE evaluated the trade-off between yield and the probability of the stock declining below B_{lim} based on alternative reductions, buffers, to the estimated harvest rate. The range of buffers used to adjust harvest limits were either based on the estimated ratio between $B_y/B_{trigger}$ and $F_y/F_{trigger}$, using either alternative fractile values of the estimated distributions from each of the quantities or the fractiles of the probability of the stock declining below the B_{lim} (termed the precautionary-approach).

The MSE results suggest that the SPiCT model with a precautionary-approach advice rule (fish at F_{MSY} unless there is greater than 5% probability that the predicted biomass is below B_{lim} termed MSY-PA-95) performs well for the range of life-history types examined in this analysis when model convergence is attained without the use of priors. In situations where informative priors are required for model convergence, SPiCT may underestimate uncertainty, and in this situation an additional level of precaution when setting harvest limits should be considered. Based on the assumptions applied in the MSE, the MSY-PA-97 with the stability clause performed well at reducing the probability of declining below B_{lim} while attaining higher yields. The application of a stability clause of $\pm$50% was recommend across all SPiCT advice rules.

2. MSE testing of WKMSYCat34 catch rules in FLR and linking performance to life-history traits

This research addressed ToR (a-ii). Advice rules of the form $C_{y+1} = C_{current}rfb$, where C is the catch, r is an indicator of population trend based on an index of abundance, f is an estimate of fishing mortality relative to a reference point, and b is an multiplier to reduce catch when the index is below a reference level ($I_{trigger}$), was tested in the FLR MSE framework for 29 ICES category 3 & 4 stocks.

Discussions of the initial results lead to several further analyses that were explored throughout the workshop:

1) The recruitment process error (σ_R) in the initial simulations was fixed at a relatively low level. Interannual variability of recruitment deviations can be very high for some species, and it was recommended that further simulations be conducted with higher levels of recruitment error to evaluate the performance of the advice rule under these conditions.

2) The operating models for the 29 stocks rely on the Gislason equation to link natural mortality (M) at size to the von Bertalanffy growth parameters, resulting in very high correlation between adult M and the von Bertalanffy K parameter. Further simulations were recommended where adult M was decoupled from K with the aim of i) examining the influence of higher natural

mortality on juvenile fish and ii) discriminating between the influence of *M* and *K* on the performance of the control rule.

3) Further simulations were run assuming perfect information to identify individual contributions of the three components in the catch rule. Particularly important was the $I_{trigger}$ reference point, which by default was set as 1.4 times the lowest point in the index of abundance. The results found that the performance of advice rule improved when $I_{trigger}$ was set to the true $0.5B_{MSY}$. Further research is required to identify robust reference levels for $I_{trigger}$ for data-limited situations where the index at $0.5B_{MSY}$ is not known.

4) Elasticity analysis was requested to identify the influence from each component of the harvest control rule (*rfb*) over the simulated projection period for each of the 29 simulated stocks. The intention of this request was to provide further insight in the performance of the harvest control rule based on the assumed life-history dynamics.

The initial results and further simulations conducted during the workshop demonstrated that a single advice rule of the form tested here is unlikely to perform well for the full range of life-histories in the ICES category 3 & 4 stocks. Different patterns in the time-series of index of abundance and mean length data that arise due to different life-history and fishing dynamics, mean that some components of the advice rule are likely to be more informative under certain conditions than others. Alternative weightings of the advice rule components, variable lags in the data streams, and the use of different amounts of historical data in the advice rule were recommended to identify variants of the advice rule that work for certain classes of fishery dynamics. Some initial explorations of this nature were conducted during the workshop, but further research is required to adequately explore these issues.

3. MSE testing short-lived species

This research addressed ToR (b-i) and involved MSE testing of different catch rules based on survey trends for short-lived species (anchovy and sardines). The analyses examined the performance of the control rules under different conditions of interannual variability of recruitment and levels of observation error and using different amounts of historical data in the control rule. The results of these analyses demonstrated the need for quick responsiveness in managing short-lived species, and that the performance of the control rule deteriorated as a longer time-series of historical data was used. Recommendations were made for modifying the presentation of the results to make interpretation of the results easier. There were no recommendations for substantial modification of the structure or assumptions of the model. However, the performance of the harvest control rules and the uncertainty cap differed between the simulated anchovy and sardine stocks. A specific workshop evaluating the application of harvest control rules for a range of short-lived species, examining the time-lag in the historical data included in the index trend and evaluation of the uncertainty cap (e.g. the percentage the catch could either increase or decrease between years) is recommended.

4. MSE testing of catch rules for elasmobranchs

This research addressed ToR (a-ii) and investigated the performance of a control rule using length-based indicators to manage elasmobranch fisheries within an MSE framework. An operating model was built based on the Cuckoo ray from the Irish Sea, with alternative scenarios for size of capture relative to size of maturity and harvest control rules. Discussions during the workshop resulted in the following recommendations:

1) The steepness of the stock–recruitment relationship is important for determining the appropriateness of the SPR reference points used in the control rule. An alternative parameterisation of the stock–recruitment relationship developed specifically for elasmobranch life histories was suggested and included in further simulations.

2) The reliability of the observed size distribution used in the control rule is influenced by the sample size, with the rarer larger individuals likely to be underrepresented if the sample size is small. Further simulations were conducted to evaluate the effect of sample size on the performance of the control rule. These results indicated that the control rule behaved more biologically precautionary when sample size was low.

3) Further simulations were also carried out to evaluate the influence of observation error in the CPUE index. These results demonstrated that an asymmetric constraint on the catch limit was required when there was high uncertainty in the CPUE index.

The results from initial and further simulations conducted during the review indicated that the performance of the harvest control rule is sensitive to the data quantity, data quality, the exploitation of immature individuals, and the stability cap. The probability of the stock declining below SSB thresholds was reduced when the harvest control rule included both information from the trend in the CPUE and the mean length ratio. Across simulations the stock had the highest probability of declining below SSB thresholds when immature individuals were captured by the fishery indicating that a more precautionary harvest control rule would be warranted in this situation. Further work should explore the performance of the harvest control rules on other elasmobranch stocks since life histories can vary widely. Additionally, further simulation work should condition the operating model based on observed fishery data to ensure that conclusions reached are consistent with the true nature of the fishery and data.

Recommendations for future research

The following recommendations should be considered for future research involving MSE of catch-rules for ICES data-limited fisheries:

1) MSE convergence diagnostics should be developed to determine if enough simulations have been run to result in stable performance statistics, and to avoid running more simulations than necessary.

2) The terms of reference state that the analyses should determine if the performance of the advice rules is correlated with life-history characteristics. Life-history parameters are rarely known with any certainty, especially for data-limited fisheries. Therefore, it is important to explore the full range of uncertainty within the MSE to ensure that the selected advice rule is robust to the uncertainty that exists in the fisheries where it will be implemented. For example, further research could examine:

   2.1) A systematic evaluation of different recruitment patterns such as different levels of recruitment compensation ('steepness') and recruitment process error and identify the conditions where advice rules perform well and where they are likely to fail.

   2.2) A wider range of life-history types than those generated using empirical relationships linking the fundamental life-history parameters. For example, the Gislason equation results in the adult natural mortality rate (*M* when length ≈ asymptotic length) to be essentially equal to von Bertalanffy K parameter (see Figure 1 and R code below), which represents a specific type of life-history pattern, and does not include the diversity observed in fish populations. While empirical relationships are convenient for constructing operating models, future MSE research should account for the considerable variability and uncertainty that exists in the life-history parameters of the data-limited stocks.

3) In addition to the wide variety of life histories of fish species, fisheries also vary widely in terms of fishery dynamics and observation processes, including the selectivity pattern of the fishing fleet(s), and reliability of the various data streams, which should be explored in detail when evaluating harvest control rules with MSE. For example, the performance on a harvest control rule may differ significantly for a stock where few immature individuals are exposed to fishing mortality compared to a fishery where almost all age and size classes are targeted. Similarly, the observation processes involved in constructing the index of abundance (e.g. hyperstability in index) or trend in mean length (e.g. influence of sample size on estimate of mean length) may influence the performance of the control rule and should be investigated before the risk of advice rule can be properly quantified.

4) Following from the previous two points, it may possible to reduce the number of species examined in the MSE by identifying distinct stock/fishery/observation categories (e.g. i) short-lived, highly depleted, high observation error, ii) long-lived, medium depleted, medium observation error, and so on for a full combination of the alternatives) and evaluating the advice rules within each scenario. This approach would identify the conditions where particular advice rules are likely to work well, and where they perform poorly. Once candidate advice rules have been selected, they can be tested on specific operating models conditioned on the data-limited fisheries where they will be applied.

5) To aid in the interpretation of the MSE results, it would be useful to ensure that the results from the different operating models are directly comparable. For example, the individual stocks can be initialized at the same biomass relative to B_{MSY} and be exposed to the same set of environmental conditions (e.g. process error). This ensures that the differences in performance of the advice rule(s) can be directly attributed to differences in the life histories of the species being examined, and not an artefact of different initial conditions or random processes. Similarly, it may be useful to evaluate the results within a time-scale related to the biology of the specific species, for example, the probability of rebuilding within *X* generation times.

6) The results of the various MSE analyses demonstrated that it is unlikely to find a single advice rule that performs well for a wide range of life-history types and fishery conditions. Further exploration of alternative advice rules, weightings of individual components within a generic advice rule, time-lags in data, and selection of amount of historical data to use, would be useful for identifying a suite of advice rules that perform well under the various fishery conditions of the ICES category 3 & 4 stocks.

7) When operating models have been conditioned on specific stocks and fisheries, it would be useful to include plots of the various data streams generated by the operating model and comparing them to the observed data from

that fishery. Additionally, the level of observation error used to generate indices of abundance or catch-per-unit-of-effort time-series should be consistent with the uncertainty in the observed data.

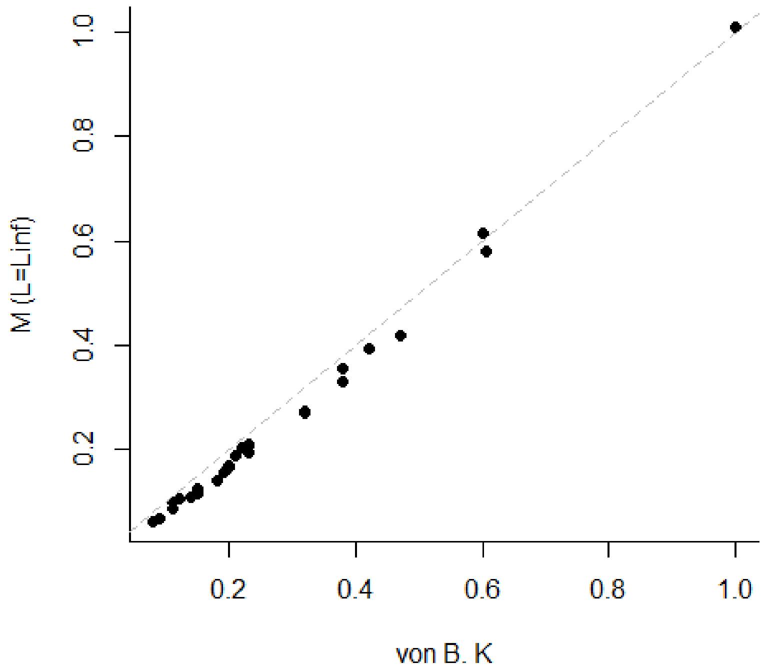

Figure 1. Scatterplot of the von Bertalanffy K parameter and the natural mortality rate (*M*) for fish at average asymptotic length (Linf). The dashed grey line indicates the 1:1 line.

R code to generate figure

LHData <- data.frame(Species = 1:29,

Linf=c(33, 85.6, 119, 50.2, 47.5, 66.7, 37, 54, 24, 48, 38, 79.9, 105.5, 106, 70, 75.14, 66.2, 123.5, 139.5, 118, 22, 50.8, 66.8, 41.25, 115.1, 58, 44, NA, 110.1),

K=c(0.606, 0.19, 0.14, 0.11, 0.21, 0.32, 0.42, 0.12, 1, 0.23, 0.38, 0.2, 0.18, 0.18, 0.2, 0.15, 0.23, 0.15, 0.09, 0.14, 0.6, 0.47, 0.32, 0.22, 0.11, 0.38, 0.23, 0.44, 0.08),

t0=c(NA, NA, NA, 0.08, NA, 0.29, NA, NA, NA, NA, -1.01, -0.36, -0.38, NA, NA, -0.96, -0.71, NA, -1.84, -0.88, NA, -1.47, -0.46, -1.16, -0.39, -0.27, NA, NA, 0.39))

GislasonM <- function(L, Linf, K) exp(0.55-1.61*log(L)+1.44*log(Linf)+log(K))

LHData$AdultM <- GislasonM(LHData$Linf, LHData$Linf, LHData$K)

plot(LHData$K, LHData$AdultM, bty="l", xlab="von B. K", ylab='M (L=Linf)', pch=16)

abline(a=0, b=1, col="grey", lty=2)

Annex 7: Recommendations

Recommendation	For follow up by:
It is recommended by WKLIFE VIII that there be a ninth meeting of WKLIFE in Lisbon, Portugal 30 September–4 October 2019 whose ToRs should be discussed by ACOM at their November 2018 consultation meeting.	ACOM
The performance of the 3.2.1 catch rule can be improved in terms of risk by applying a multiplier. Last year in WKLIFE VII, based on a limited number of simulations (only four representative stocks), a multiplier of 0.95 was proposed independent of k. This year, to keep the probability of dropping below Blim to 5% or less, and based on a larger number of stocks representing a wide range of life-history characteristics, simulations indicated a revision of this proposal incorporating k. If a multiplier were to be used independent of k, a multiplier of no greater than 0.8 is recommended. If a multiplier were to be used depending on the value of k, then for k values in the range of 0.08–0.19, a multiplier of no greater than 0.85 is recommended, and for k values in the range of 0.20–0.32, a multiplier of no greater than 0.90 is recommended. For k values above 0.32, the 3.2.1 catch rule should not be applied in its current form.	ACOM
Early in 2019, convene an ICES Workshop on DLS short-lived species that addresses both assessment methods; e.g. seasonal SPiCT, and long-term management strategy evaluations; building on the work of WKLIFE VII and WKLIFE VIII. Two co-chairs are recommended (Andrés Uriarte, Spain and Piera Carpi, UK). It is suggested that the workshop focus on all the short-lived stocks in Categories 3 and 4 that ICES is required to provide advice for; as identified by WKLIFE VII and WKLIFE VIII in Section 4.7 of this report.	ACOM
The approaches used within WKLIFE rely upon life-history traits and as ICES progresses towards providing quantitative catch advice and forecasts, it is important that agreed parameter values are used for the stocks that ICES provides advice for. WGBIOP should be tasked with a review of the current estimates of life-history parameters required for models explored by WKLIFE at its meetings. These are: von Bertalanffy growth function Linf (also referred to as L∞) (mm), von Bertalanffy k (yr–1), Length–weight a, Length–weight b, Natural mortality M (yr-1), and Length-at-maturity (mm).	WGBIOP
MSE convergence diagnostics should be developed to determine if enough simulations have been run to result in stable performance statistics, and to avoid running more simulations than necessary.	WKGMSE2 ACOM
A theme session be proposed for the ICES ASC in 2020; signifying ten years of development of data-limited methods within the ICES community.	SCICOM

Annex 8: WKLIFE VIII Advice Rule Guidance

Drafted by RGLIFE

Introduction

This document offers a description of the advice rules developed by WKLIFE VIII and reviewed by RGLIFE for harvest control rules and the precautionary approaches (PA) used by ICES for stocks in category 3 and 4, including their application across managed species. Additionally, a description of the harvest control rules and precautionary approaches for category 3 to 6 stocks for short-lived species and elasmobranchs is provided.

Background

The guidance for application of harvest control rules and precautionary approaches for category 3 to 6 stocks were developed at the 2018 WKLIFE VIII workshop. The objective of this workshop was to investigate the performance of harvest control rules and precautionary approaches across life-history types through simulation and MSE to identify potential approaches that could best meet the goals of management; i.e. maximizing long-term yield, in a manner that is consistent with ICES precautionary approach; i.e. having a low probability of falling below biologically sustainable limits.

Advice rules for short-term forecast utilizing a stock production model (SPiCT)

This work is with respect to WKLIFE VIII ToR a) i:

ToR a) Develop, test, and review advice rules that are in line with the ICES MSY and precautionary approaches for category 1 stocks that apply to a wide variety of ICES stocks (e.g., demersal species) in categories 3 and 4.

i) Develop assessment methods that utilize a stock production model (e.g. SPiCT) and advice rules based on a short-term forecast (Section 3.1 of WKMSYCat34 report).

Category 3 and 4 stocks that are assessed using surplus production models (e.g. SPiCT) incorporate the following components to the MSY harvest control rule to determine an annual total allowable catch (TAC):

Quantity	Definition and Purpose
$B_{y+1}/B_{trigger}$	The ratio of the estimated biomass B in the next year y +1, and the lower limit of biomass, $B_{trigger}$. $B_{trigger}$ is determined based on life history and assumed shape of the yield curve defined by the shape parameter of the stock-production curve.
F_y/F_{MSY}	The ratio of the estimated fishing rate F in year y and the estimated fishing rate that would achieve maximum sustainable yield F_{MSY}.
B_{lim}	Set equal to 0.3 B_{MSY} where B_{MSY} is the biomass level which would produce maximum sustainable yield.
PA	The probability of the biomass being above the B_{lim}.
Stability Clause	Limits the amount the TAC can change upwards or downwards between years. The recommended value is ± 50% where the TAC would be limited to increase or decrease by 50% relative to the previous year's TAC.

Application of the short-term forecast and harvest control rule

Application of harvest control rules to determine harvest limits using the output from SPiCT should be based on model performance (Figure 1).

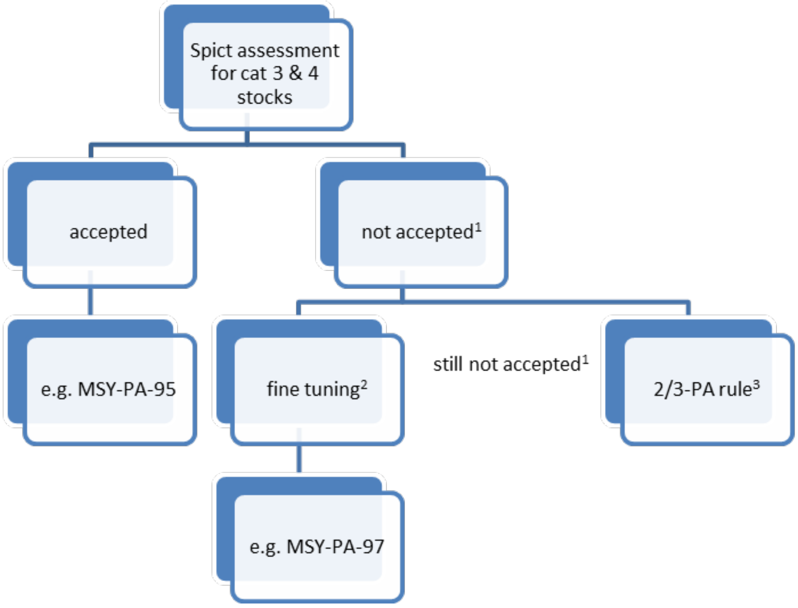

Figure 1. Decision tree defining the application of harvest control rules based on model performance and diagnostics.

An "accepted" assessment using SPiCT is defined as a model that estimates model parameters based on the data without the aid of prior information (i.e. ability to estimate the shape parameter of the stock-production curve which defines at what relative stock size MSY is achieved) and the model meets pre-specified convergence diagnostics. SPiCT forecasts the stock with a fishing rate at the estimated MSY (F_{MSY}) and calculates the probability of biomass falling below B_{lim}. If the probability of the stock biomass being above B_{lim} is less than a pre-specified value, termed *PA* buffer, the fishing rate applied in the forecast is adjusted downward (i.e., reduced forecast *F* below F_{MSY}) until the probability equals the *PA* buffer. A *PA* buffer equal to a 95% probability of the biomass being above B_{lim} is recommended for accepted SPiCT assessments. The "MSY" harvest control rule with a *PA* buffer that corresponds to a 95% probability is termed MSY-PA-95.

In situations where an assessment using SPiCT does not meet the above criteria (e.g. required to pre-specify priors to estimate the stock-production curve), it may be used to set harvest limits, but the harvest control rule should be adjusted to account for additional uncertainty. In these situations it is advised to apply a higher *PA* buffer that corresponds to a 97% probability that the stock is above B_{lim}. Applications of SPiCT which require additional model specifications to estimate harvest limits may estimate a reduced level of uncertainty, hence the selection of a higher *PA* buffer equal to a 97% probability of the stock being above B_{lim} to account for the reduced model uncertainty.

If after attempts of fine tuning an assessment using SPiCT does not result in adequate model behaviour, it is recommended to apply the 2-over-3 rule (ICES method 3.2; ICES, 2012) based on the trend in the index from the average of the two most recent years relative to the average of the preceding three years. Additionally, a *PA* buffer equal to an 80% probability that the stock biomass is above B_{lim} should be applied.

The frequency and duration of the *PA* buffer was investigated during the 2016 WKLIFE VI meeting. The recommended application can be found in the 2016 WKLIFE VI report (ICES CM 2016/ACOM:59).

It is recommended to apply a stability clause of ± 50% which allows the TAC to change up to 50% between years in all applications.

The above described application of the harvest control rule applies generally to all life-history types, but specific adjusts should be considered when applying to short-lived stocks (e.g. pilchard, anchovy) described below in the Caveats section below.

Caveats

Short-lived stocks with higher interannual variation in biomass have higher risk of the stock declining below B_{lim}. Assessment of short-lived stocks using SPiCT should use quarterly time-steps to model the dynamics of the stock. Using quarterly time-steps, allows the model to capture dynamics of the stock that management may need to be reactive to that would be missed if modelled on an annual time-step.

Advice rules for harvest control rules for length-based approaches (WKMSYCat34)

This work was done with respect to WKLIFE VIII ToR a) ii:

ToR a) Develop, test, and review advice rules that are in line with the ICES MSY and precautionary approaches for category 1 stocks that apply to a wide variety of ICES stocks (e.g., demersal species) in categories 3 and 4.

- ii) Develop assessment methods that utilize length-based approaches and advice rules of the form $C_{y+1} = C_{current}\ r\ f\ b$ (Sections 3.2.1 and 3.2.3 of WKMSYCat34 report).
  - A) Test the advice rules via Management Strategy Evaluation (MSE).
  - B) Establish whether performance of the advice rules is correlated with life-history characteristics.
  - C) If such correlations exist, develop guidelines for use of the advice rules dependent on life-history characteristics

The harvest control rule termed "WKMSYCat34" is defined as:

$$TAC_{y+1} = m * TAC_y * r * f * b$$

where the TAC for next year y+1 is based on the current year's TAC y adjusted by the following components:

Component	Definition and Use
r	The rate of change in the index based on the average of the two most recent years of data (y-2 to y-1) relative to the average of the three years prior to the most recent two (y-3 to y-5), termed the "2-over-3" rule.
f	The ratio of the mean length in the observed catch above the length of first capture relative to the target reference length.
b	Adjustment to reduce catch when the most recent index data $I_{y-1} < 1.4*I_{trigger}$. Set equal to 1 when the most recent index data $I_{y-1} > 1.4*I_{trigger}$. $I_{trigger}$ is defined as the lowest observed index value for that stock.
m	Multiplier applied to the harvest control rule to maintain the probability of declining below B_{lim} to less than 5%. May range from 0–1.0.
Stability clause	Limits the amount the TAC can change upwards or downwards between years. The recommended values are +20% and -30% where the TAC would be limited to increase by 20% or decrease by 30% relative to the previous year's TAC.

Each component of the harvest control rule is applied in tandem in order to determine next year's catch advice by adjusting upwards or downwards this year's catch advice, based on the trend in the index (i.e. is the stock going up or down, r), the observed mean length in the catch relative to the target mean length (f), and a factor to adjust catch downwards if the current stock falls below a threshold index value (b), defined as $1.4*I_{trigger}$. $I_{trigger}$ is defined as the lowest observed index value for that stock. The multiplier (m) is then applied as a precautionary measure to ensure that the probability of the stock declining below B_{lim} is less than or equal to 5%.

The performance of the catch rule is driven largely by three factors:

1) The life history of the species.

2) The trend in the index being a good measure of the current status of the stock based on the life history.
3) The $I_{trigger}$ value being defined at or near the true threshold level (e.g. 0.5B_{MSY}).

The multiplier applied in to the WKMSYCat34 harvest control rule should be selected based on the first two factors described above.

Application of the harvest control rule

Incorporating a multiplier can improve the performance of the harvest control rule in terms of risk (i.e. reduced probability of the stock declining below B_{lim}) by buffering against the uncertainty of each component of the harvest control rule adequately reflecting the true state of the stock resulting in the correct management action. The risk of the stock declining below B_{lim} is related to the life-history dynamics of the stock. It is recommended that the application of the harvest control rule include a life-history based multiplier to reduce risk.

Harvest estimate for longer-lived stocks with low natural mortality and low growth rates (i.e. von Bertanlaffy k < 0.19; e.g., rose fish, ling) should apply a multiplier to the harvest control rule of 0.85 where the estimated next year TAC would be set equal to 85% of the estimated yield based on the harvest control rule ($TAC_y = 0.85 * TAC_{y-1}*r*f*b$). Medium-lived stocks with growth rates between 0.20–0.32 (e.g. plaice, red mullet) should apply a multiplier no greater than 0.90 to next year's estimated TAC.

The harvest control rule is not recommended to be used for short-lived stock with fast life-history dynamics (i.e. k > 0.32; e.g. sardine). The 2-over-3 (r) component of the harvest control rule does not adequately capture the trend in biomass for life-history dynamics with high interannual variability because the trend in biomass over the last two years relative to the preceding three years may not be indicative of current stock conditions. However, if this harvest control rule is applied to short-lived stocks with k > 0.32 it is recommend that the harvest control rule should apply a shorter period to calculate the trend in the index, 1-over-2, with a reduced multiplier, no greater than 0.80, to determine a TAC.

It is recommended to apply a stability clause of +20% and -30% where the TAC would be limited to increase by 20% or decrease by 30% relative to the previous year's TAC in all applications of the harvest control rule.

Caveats

The harvest control rule has variable performance (i.e. maintaining the stock near the target biomass and reducing the risk of the stock declining below B_{lim}) based on life-history traits of the species and the $I_{trigger}$ (harvest control rule component $b = 1.4*I_{trigger}$) level when a multiplier of 1 was applied to the harvest control rule.

The $I_{trigger}$ component of the harvest control rule should be set at a point that if the stock declined below could result in an undesirable state of the stock (i.e. declining below B_{lim} resulting in reduced yield and increased probability of stock collapse). Often, 0.5B_{msy} is identified by fisheries management as that limit. The harvest control rule, generally, maintained stock at or near target biomass for slow and medium life-history types when the $I_{trigger}$ value was set equal to 0.5B_{msy}. Setting $I_{trigger}$ equal to the lowest observed index value may not perform well if the stock has not been heavily exploited or the index period does not cover a period of low biomass levels in the stock. In these instances the harvest control rule may be overly precautionary. The $I_{trigger}$ component of the harvest control rule should be reflective of a true limit biomass level for the stock in question. Care should be used when determining this value based on the stock productivity and susceptibility of the stock to impacts from fishery-specific activities.

Advice rules for harvest control rules for short-lived species for category 3 to 6

This work was done with respect to WKLIFE VIII ToR b) i:

ToR b) Develop, test, and evaluate assessment methods and on the basis for an advice rule for category 3 to 6 stocks for short-lived species.

i) Consider the need for specific advice rules for these stocks, and if needed, test these advice rules via MSE.

The risk of harvesting short-lived stocks that have high interannual variability in biomass is inherently higher given their dynamics. Due to this, harvest control rules applied for setting harvests of short-lived stocks need to be designed in such a manner that incorporates the dynamics of these stocks and an appropriate level of precaution. Guidance is provided for harvest control rules for short-lived stocks that determine next year's catch based on the previous year's catch, and the trend in the index with a cap on the amount that the catch can very between years based on the uncertainty within the survey index (termed "uncertainty cap").

The harvest control rule is defined as:

$$TAC_y = TAC_{y-1} \frac{I_y}{\sum_{y-1}^{y-2} I_y/2}$$

where the TAC for the current year is based on last year's TAC adjusted by the trend in the index, I_y, in the current year y relative to the average of the index value in the previous two years. An uncertainty cap is applied to limit the change in the index trend, the I_y component of the harvest control rule, to ± 80% which allows the current year's TAC to increase or decrease up to 80% relative to the previous year's TAC.

Application of the harvest control rule

The harvest control rule for short-lived stock is composed of three components: the catch in the previous year, the trend in the index, and the uncertainty cap. The trend in the index performs best for short-lived stocks when the most recent years, including data from the current year, are applied. It is recommended to use the most recent year of data divided by the average of the index over the preceding two years, termed 1-over-2.

Short-lived stocks with high interannual variability in biomass can have large swings in biomass from one year to the next. Given this, the harvest control rule should be able to be adjusted accordingly from year to year by applying an 80% uncertainty cap. The uncertainty cap governs the percentage that the catch advice can change between years. Large reductions in catch may be necessary between years to respond accordingly to reductions in the underlying stock biomass. An uncertainty cap of 80% allows the catch advice to change up to 80% from one year to the next.

Cautions

The above harvest control rule based on the trend in the index, 1-over-2, and the associated uncertainty cap performed well at reducing the probability of the simulated stocks declining below B_{lim}. In contrast, the WKMSYCat34 harvest control rule ($TAC_{y+1} = m * TAC_y * r * f * b$) is not recommended to be used for short-lived stocks with fast life-history dynamics (i.e. $k > 0.32$; e.g. sardine). The 2-over-3 (r) component of the harvest control rule did not adequately capture the trend in biomass for life-history dynamics with high interannual variability in biomass because the trend in biomass over the last two years relative to the preceding three years may not be indicative of current stock conditions. However, if the WKMSYCat34 harvest control rule is applied to short-lived stocks with $k > 0.32$, it is recommend that the harvest control rule should apply a shorter period to calculate the trend in the index, 1-over-2, with a reduced multiplier, no greater than 0.80, to determine a TAC.

Advice rules for bycaught elasmobranch stocks

The TAC for bycatch elasmobranch stocks is defined as:

$$TAC_{y+1} = TAC_y * r * f$$

where the components are defined as:

Component	Definition and use
r	The rate of change in the catch per unit of effort (CPUE) based on the average of the two most years of recent data (*y*-2 to *y*-1) relative to the average of the five years prior to the most recent two (*y*-3 to *y*-8), termed the "2 over 5" rule.
f	The ratio of the mean length in the observed catch above the length of first capture relative to the target reference length.
Stability clause	Limits the amount the TAC can change upwards or downwards between years. The recommended values are +5% and -25% where the TAC would be limited to increase by 5% or decrease by 25% relative to the previous year's TAC.

Application of the harvest control rule

The performance of the harvest control rule is dependent on the accuracy of the CPUE and correctly determining the target reference length. The CPUE is used to identify the trend in the biomass relative to previous years. Determining the trend in biomass based on the CPUE performed well when the average of the previous two years relative to the average of the preceding five years (e.g. 2-over-5) were used. Elasmobranch species generally have lower natural mortality rates and low fecundity compared to fish species and, hence, a longer time-period capturing the trend in biomass performed better compared to the 2-over-3 approach. Additionally, applying the longer term index rule reduced risk when there was increased uncertainty in the CPUE data.

If possible, the fishery should be managed such that the length of first capture is greater than the length of maturity for bycaught elasmobranch species. The *f* component of the harvest control rule adjusts the TAC upwards or downward based on the average length of captured individuals relative to the target length, based on biology and life history. The harvest control rule will result in lower TAC limits if the fishery is selecting a large proportion of immature individuals.

Elasmobranch species are often slow growing with low fecundity making them slow to recover if over-exploited. Based on this, an asymmetric stability clause governing the percentage of change allowed in the TAC between years is recommended. The harvest control rule should be able to apply larger reductions to the TAC based on the CPUE and length data when warranted relative to amount allowed for increases in the TAC. It is recommended to apply an asymmetric stability clause which allows for reductions up to 25% downwards or an increase up to 5% in the TAC for next year relative to the current year's TAC.

Caveats

Several factors can impact the performance of the harvest control rule for elasmobranch stocks. Elasmobranch species often have dimorphic growth between the sexes. It is recommended to calculate the target reference length based on the biology of the larger growing sex. Additionally, if the fishery is exploiting primarily immature individuals, the sustainable catch from the population will be lower and the TAC will be reduced based on the harvest control rule.

As bycatch species, the performance of the harvest control rule is dependent upon the data from the target fishery to adequately capture the dynamics of the bycaught stock. Uncertainty in the CPUE can result in these data being less informative regarding the trend in elasmobranch stocks. Additionally, uncertainty in length measurements (i.e. observation error) and limited sample sizes can result in the harvest control rule being more reactive to non-representative length samples resulting in unwarranted reductions or increases in the TAC.